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Research Article

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Collaborative Navigation as a Solution for PNT Applications in GNSS Challenged Environments – Report on Field Trials of a Joint FIG / IAG Working Group

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Abstract: PNT stands for Positioning, Navigation, and Timing. Space-based PNT refers to the capabilities enabled by GNSS, and enhanced by Ground and Space-based Augmentation Systems (GBAS and SBAS), which provide position, velocity, and timing information to an unlimited number of users around the world, allowing every user to operate in the same reference system and timing standard. Such information has become increasingly critical to the security, safety, prosperity, and overall qualityof-life of many citizens. As a result, space-based PNT is now widely recognized as an essential element of the global information infrastructure. This paper discusses the importance of the availability and continuity of PNT information, whose application, scope and significance have exploded in the past 10–15 years. A paradigm shift in the navigation solution has been observed in recent years. It has been manifested by an evolution from traditional single sensor-based solutions, to multiple sensor-based solutions and ultimately to collaborative navigation and layered sensing, using non-traditional sensors and techniques – so called signals of opportunity. A joint working group under the auspices of the International Federation of Surveyors (FIG) and the International Association of Geodesy (IAG), entitled 'Ubiquitous Positioning Systems' investigated the use of Collaborative Positioning (CP) through several field trials over the past four years. In this paper, the concept of CP is discussed in detail and selected results of these experiments are presented. It is demonstrated here, that CP is a viable solution if a 'network' or 'neighbourhood' of users is to be positioned / navigated together, as it increases the accuracy, integrity, availability, and continuity of the PNT information for all users.

Keywords: GNSS, Ubiquitous Positioning, Continuous PNT, Collaborative Positioning, Multi-Sensor Systems, Integrated Navigation

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1 Introduction and Motivation

Numerous civilian and military applications, including, intelligent transport systems (ITS), location based services (LBS) and personal navigation systems are heavily dependent on the availability of Global Navigation Satellite Systems (GNSS) signals. Hence, the provision of robust navigation and timing (PNT) information is critical for many application. An essential question is: what are the users looking for? In fact, the user is, generally, not focused on how the PNT information is obtained, but that it is provided reliably and continuously with the accuracy suitable for the application. For a growing number of users, navigation should be done in the background; it ought to serve its purpose, and it should not be the objective by itself. Consider smartphones; they can track themselves with the use of digital maps and location sensors and services, and are also capable of tracking other smartphones (a network of users?) [18].

Finding the correct balance between the performance (availability, continuity, accuracy and integrity) and cost is a significant challenge for many applications such as ITS and LBS. GNSS has become the primary means of obtaining positioning solutions, enabling users to easily compute their positions, at a global scale, with an achievable accuracy of between 5 to 15 m. The major drawback of GNSS, however, is that it requires an open-sky view and therefore does not work in dense urban environments, tunnels, underground car parks etc. In such situations, differential GNSS, external sensor systems or mobile communications network-assisted techniques may be used to enhance partial, stand-alone GNSS performance. Also, for certain applications, the use of other sources of available information, such as receiver elevation obtained from a digital terrain model (DTM), may potentially only recover a small fraction of the missing or bad GNSS observables [5]. Hence, relying on GNSS alone may not always be sufficient for critical applications such as vehicular collision avoidance systems, emergency response and autonomous vehicles. Also, these applications typically need sub-metre and potentially even centimetre level accuracy, and high update rates (>10 Hz), which are not achievable using standalone GNSS solutions [45].

To overcome the shortcomings of GNSS PNT the concept of Collaborative Positioning (or also referred to as cooperative positioning) CP has been developed, to further improve the navigation capability of a group of users. Collaborative positioning techniques leverage the availability of a communications infrastructure to share information and data between objects within a neighbourhood. Developed originally for use across wireless sensor networks, CP techniques offer a viable solution for improving positioning for land mobile applications. CP is a logical evolution of the multi-sensory navigation approach that has developed over the last few years, where GNSS augmentation was provided for each individual user by sensors such as Inertial Measurement Units (IMU's), barometers, magnetometers, odometers, or digital compasses, for applications ranging from pedestrian navigation, to georeferencing of remote sensing sensors in land-based and airborne platforms. The simple objective of much of the CP research is to develop an algorithm, which will provide an optimum navigation solution for all networked users for which a navigation solution is possible. Hence, CP can increase the accuracy, integrity, availability, and continuity of the positioning solution. The information shared between the users, or between sensor platforms, can be in the form of inter-nodal ranges, relative speed, orientation, and satellite related data.

The work presented in this paper is an initiative of a joint working group on 'Ubiquitous Positioning Systems' within the International Federation of Surveyors (FIG), Commission 5 and the International Association of Geodesy (IAG), Commission 4. The foci of the working group are the performance characterisation of positioning sensor technologies that can play a role in the development of ubiquitous positioning systems; the theoretical and practical evaluation of current algorithms for measurement integration; the development of new integration algorithms and innovative modelling techniques and the generation of formal parameters that describe the performance of emerging technologies.

A series of field experiments related to the concept of CP and navigation were performed at the University of Nottingham in May 2012. In this paper, a discussion of the importance of robust PNT information in our daily lives is presented in section 2. An introduction and description of the CP concept is presented in section 3. The test platforms, field experiments and selected results are given in sections 4 and 5 respectively. Finally, in section 6 some concluding remarks and an outlook on future work are given.

2 Importance of Continuous Position, Navigation and Timing (PNT)

Over the last 10 to 15 years the application, scope and significance of PNT information have exploded. Space-based PNT refers to the capabilities enabled by GNSS, possibly enhanced by Ground and Space-based Augmentation Systems (GBAS and SBAS). Collectively, the space-based PNT capabilities provide position, velocity, and timing information to an unlimited number of users around the world, allowing every user to operate in the same reference system and timing standard. Such information has become increasingly critical to the security, safety, prosperity, and overall quality of life of many citizens. As a result, space-based PNT is now widely recognized as an essential element of the global information infrastructure. Examples showing the growing importance and necessity of continuous PNT information are:
- Intelligent Transportation Systems (ITS),
- Vehicle collision avoidance systems,
- Personal / pedestrian navigation (PN),
- Location-Based services (LBS),
- Air traffic management,
- Unmanned, and autonomous land-based and aerial vehicles (UAVs) navigation for mapping and surveillance (this application extends to land and underwater applications),
- Navigation and guidance of teams of robots, etc.,
- Emergency response and rescue operations in large warehouses, multi-storey buildings, train / metro stations, airports, etc.,
- First responders and fire-fighters,

– Dismounted soldier navigation,
– Asset location and tracking,
– Precision farming.

Consequently, robust PNT plays a vital role in these applications. Another example of a growing importance of PNT is in utilization of wireless communication systems and mobile computing. Global PNT combined with the proliferation of wireless technologies, mobile computing devices and mobile Internet has fostered a new growing interest in location-aware systems and services. The PNT systems supporting these applications are becoming increasingly multi-sensory.

2.1 Requirements for Continuous PNT

Robust positioning is typically described in terms of performance metrics including accuracy, availability, continuity and integrity. These metrics have been fully defined in the aviation community where safety critical needs have mandated requirements for standards of positioning performance. Similar trends are evidenced in the maritime sector with the international maritime organisation (IMO) developing standards for positioning based on current and future capabilities of GNSS. The land mobile sector, however, has lagged significantly behind with the adoption of similar performance based standards and there are currently no formal specifications for land-based applications. The emerging capabilities of Cooperative Intelligent Transport Systems (C-ITS) have significantly changed the landscape for positioning information and in particular, positioning quality. C-ITS are driving the development of an increasing range of safety and liability critical applications that will require certain levels of positioning performance in order to realise the maximum benefits for improving road safety and efficiency of the road network.

In aviation (see e. g. [32]), for instance, the metrics used to describe positioning quality are the aforementioned parameters: accuracy, integrity, continuity and availability. Accuracy is defined as the degree of conformance of an estimated or measured position at a given time to a defined reference value. Integrity relates to the level of trust that can be placed in the information provided by the navigation system. It includes the ability of the navigation system to provide timely and valid warnings to users when the system must not be used for the intended operation or phase of flight. Specifically, a navigation system is required to deliver a warning (an alert) of any malfunction (as a result of a set alert limit being exceeded) to users within a given period of time (time-to-alert). Continuity of a navigation system is its capability to perform its function without non-scheduled interruptions during the intended period of operation. Availability is defined as the percentage of time during which the service is available (i. e. reliable information is presented) for use taking into account all the outages whatever their origins. The service is available if accuracy, integrity and continuity requirements are satisfied.

What is evident across these definitions is that their computation is based on the availability of sufficient measurements that not only facilitate computation of the position solution but typically will enable the identification and potential rejection of incorrect or spurious measurements. To ensure that sufficient measurements are available the majority of positioning solutions rely on the integration of multiple sensors and signals. These hybrid solutions typically integrate GNSS with measurements from inertial navigation sensors or similar in-vehicle sensor systems. Over periods of prolonged GNSS outages, as experienced in dense urban environments, the error characteristics of these sensors mean that in many cases simply integrating additional measurements will not improve the overall outcome.

Driven by the availability of Dedicated Short Range Communications (DSRC) for vehicle to vehicle and vehicle to infrastructure communications, the shortcomings of GNSS in C-ITS can be addressed using CP techniques. In such cases, vehicles within a vehicular *ad-hoc* network (VANET) share positioning related information with other vehicles or the surrounding infrastructure, in an attempt to try to improve their positioning solutions. Figure 1 shows a CP concept for VANET ITS applications. For vehicle collision avoidance systems, for instance, a navigation-to-navigation (Nav2Nav) approach is required to reduce road accidents. Hence, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications must be established. Thus, ITS include telematics and all types of communications in vehicles, between V2V, and between vehicles and fixed locations (e. g. V2I). The sharing of information between vehicles can only be achieved through the availability of a communications infrastructure that supports information exchanges between vehicles in the VANET and / or between vehicles and roadside infrastructure. The backbone of this approach is the widespread availability and use of navigation systems with no additional installation requirement, as well as the availability of map databases in navigation systems, which support map matching and predictive navigation.

However, ITS are not restricted to Road Transport – they also include the use of information and communication technologies (ICT) for rail, water and air transport, including navigation systems. The mission

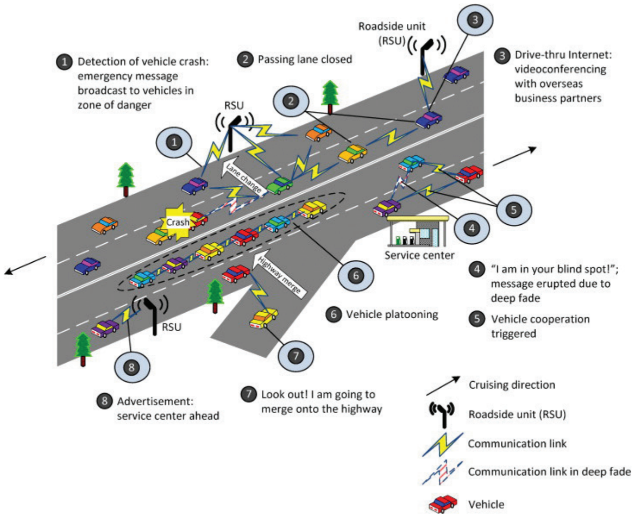

Figure 1: Positioning concept for VANET ITS applications (from Intelligentdots cited in [25]).

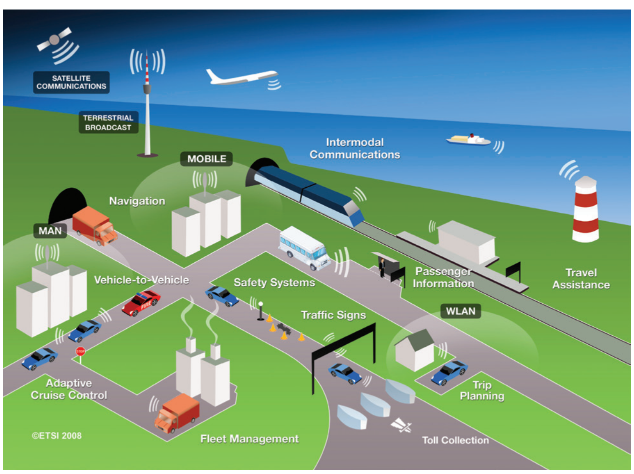

Figure 2: Cooperative system applications including all types of communications (from ETSI[1]).

of ETSI's Technical Committee Intelligent Transport Systems (TC ITS)[1] is the creation and maintenance of standards and specifications for the use of information and communications technologies in future transport systems in Europe. As illustrated in Figure 2, the various types of ITS rely on radio services for communication and use specialized technologies.

For air traffic management an evolution from a ground-based system of air traffic control to a satellite-based system has to be achieved. To realise this goal, aviation-specific applications of the existing technologies that provide PNT, such GNSS and its integration with other navigation technologies, and associated technological innovations in weather forecasting, data and sensor networking and digital communications, must be developed. Modern navigation, positioning and imaging techniques are integrated, and networked, to provide reliable location and tracking of objects, vehicles and people, as well as for obstacle avoidance. Applications of state-of-the-art technologies in air traffic management, airport operations and infrastructure management will, according to the Federal Aviation Administration (FAA), "allow more aircraft to safely fly closer together on more direct routes, reducing delays and providing unprecedented benefits for the environment and the economy through reductions in carbon emissions, fuel consumption and noise."

PNT is also an indispensable part of navigation of unmanned land-based and aerial vehicles (UAVs or nowadays referred to as Unmanned Aerial Systems UASs). It is expected that the use of unmanned platforms will rapidly grow in the future, as the regulatory issues are expected to be eased, and, ultimately resolved. This is particular significant in the case of UAVs, according to the FAA NextGen program.[2] By the end of 2013 a roadmap for the use of UAVs was announced by the FAA with special mitigations and procedures to safely accommodate limited UAS access to the US airspace.[3] Six test sites are now being established in the US. In the European Union the institutional situation is much more complex as each member state has its own regulations. Information about the EU roadmap may be found in this document[4] and on a new designated website about Remotely Piloted Aircraft Systems (RPAS).[5] Further information about UAS regulations and technologies has been published in Coordinates magazine issue No. 1, Vol. X in January 2014.[6]

Another important application area for PNT is precision farming. The concept of the "farm of the future" is enabled by accurate and continuous PNT and other geospatial technologies and infrastructure. Hence, precise PNT is required anywhere in the world, at all times, for automated and autonomous farm machinery navigation and precision application of seed, water, fertiliser and pesticides. The farm's operation is facilitated by remote sensing and GNSS, integrated into a GIS, to measure and

1 http://www.etsi.org/index.php/technologies-clusters/technologies/intelligent-transport

2 http://www.faa.gov/nextgen/; http://www.faa.gov/news/press_releases/news_story.cfm?newsId=15334

3 http://www.faa.gov/news/press_releases/news_story.cfm?newsid=15334

4 http://easa.europa.eu/certification/docs/policy-statements/E.Y013-01_%20UAS_%20Policy.pdf

5 http://ec.europa.eu/growth/sectors/aeronautics/rpas/index_en.htm

6 http://mycoordinates.org/uav-yet-to-fly-high/

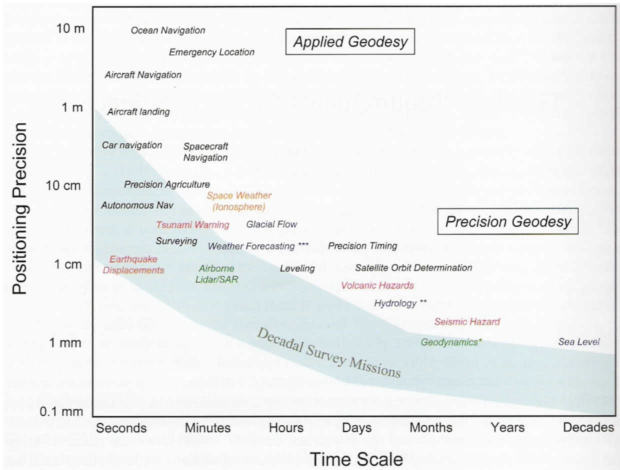

Figure 3: Precision of the current geodetic applications as a function of the required time interval (courtesy of National Research Council (NRC) of the National Academies, USA).

monitor soil moisture and yield. Local GNSS networks help to improve weather forecasting, accurate terrain elevation and land cover information integrated with a GIS for agronomy applications such as complex crop management.

The precision requirements of current PNT applications, as a function of the required temporal interval, is illustrated in Figure 3. Note that the positioning scale is in powers of 10 and that range of geodetic applications spans approximately nine orders of magnitude in the time scale. Clearly, most of the engineering and navigation applications require both high accuracy and real-time availability on a continuous basis. The most demanding applications at the shortest time interval include GNSS / GPS seismology and tsunami warning systems. At the longest time intervals, the most demanding applications include sea level change and geodynamics. Applications such as the navigation of aircrafts are on the few meter level whereby the highest precision is required for landing – especially in height. For

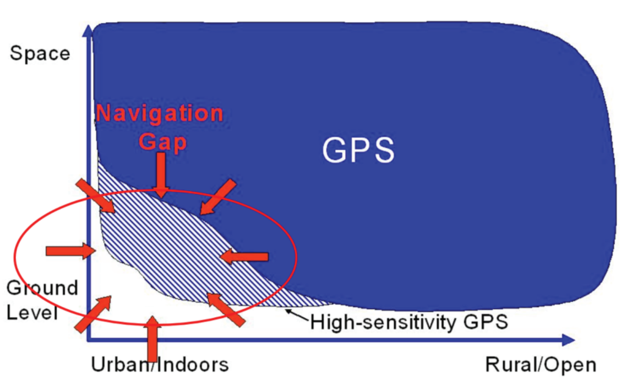

Figure 4: The GNSS navigation gap (courtesy of Prof. John Raquet, Air Force Institute of Technology (AFIT), USA).

vehicle navigation the required positioning precision is on the dm level and higher for autonomous navigation.

Some applications listed in Figure 3 happen in GNSS-challenged environments, where GNSS signals may be of inadequate availability, limited accuracy and / or continuity, or may not be available at all. In other words it can be said that these applications operate within the so-called GNSS navigation gap as illustrated in Figure 4. The applications enumerated in the beginning of this section which require continuous PNT operate largely in this gap. In the following, the challenging use case of autonomous navigation is picked as one example demonstrating that a CP solution (see section 3) is an essential part of such an application.

2.2 Autonomous Navigation Challenges

Solving the autonomous navigation problem will result not only in operational infrastructure development and the necessary regulatory issues, but also in a multitude of engineering and technical breakthroughs in sensing and control (amongst other areas). As far as the PNT component is concerned, the exploitation of multi-sensory data acquired on the platform as well as inter-platform information exchange, which is used for both navigation and geospatial data acquisition, are expected to evolve rapidly. It can be argued that the ultimate holy grail of unmanned systems is autonomous operation, which means that an unmanned vehicle should be able to complete tasks without direct control from a human operator. Autonomous operation would fundamentally revolutionise many aspects of our way of life. One of the most fundamental autonomous behaviours in navigation is getting from point A to point B without human intervention. This task may sound very simple, considering a widespread availability of GNSS, but in fact, it is a very difficult and multi-faceted problem. In real-world applications an autonomous platform must operate in an unstructured environment, deal with other users of the land-based transportation network or air space, detect terrain formations and man-made obstacles, maintain a roll-over stability, manage power, communications with other systems around it, and cope with numerous other factors.

In land-based autonomous navigation, high accuracy and reliable PNT information is essential for lane tracking, car following, intersections, passing, obstacle avoidance, parking and dynamic route planning. Some of the ongoing research trends are:[7]

7 http://www.quantumsignal.com/robotics/autonomous_navigation/

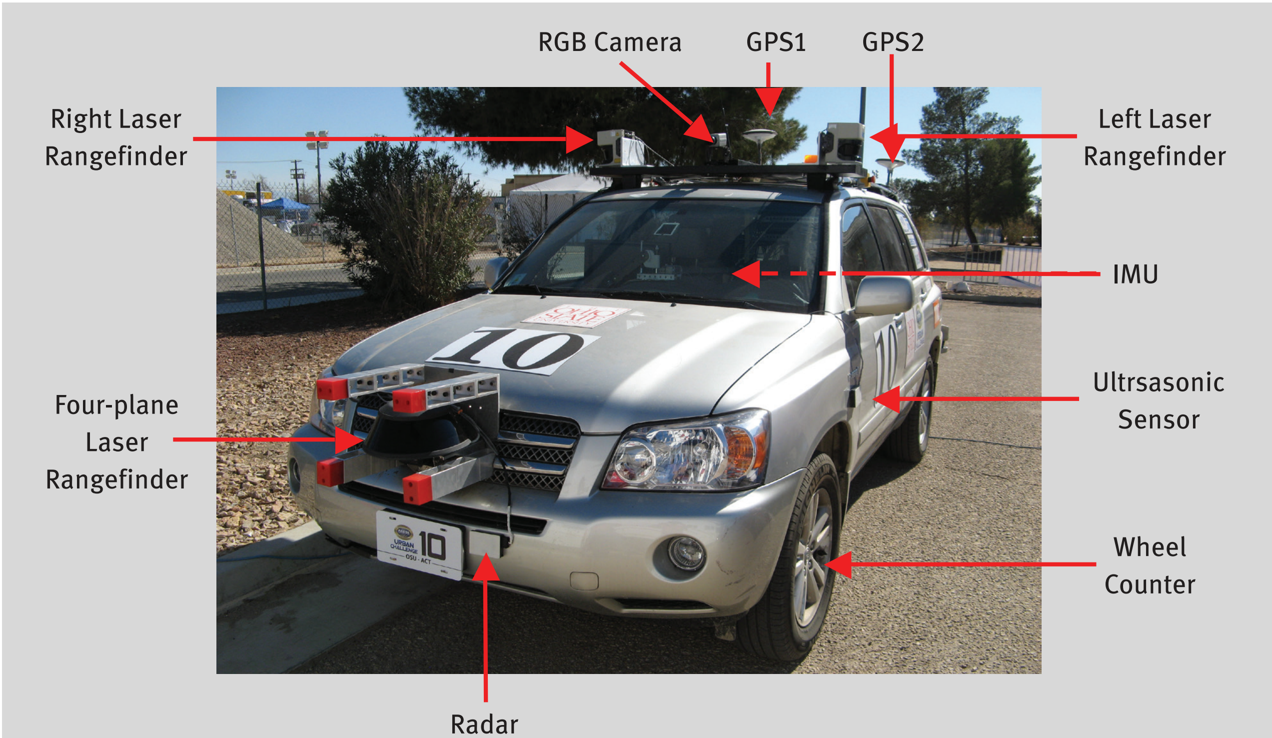

Figure 5: Essential parts of DARPA Challenges OSU ACT 2007.

- Image-based navigation or visual odometry – a technology for estimating robot position and orientation based on analyzing of camera (vision) data;
- Terrain-based navigation and terrain sensing – technologies for autonomously sensing and analyzing surface, terrain characteristics and other components of environment to locate and navigate; and
- Mobility prediction – leveraging sensed environment and terrain information and new, advanced algorithms to analyse robotic traversability.

Figure 5 illustrates an example of an autonomous land-based vehicle built at Ohio State University OSU ACT (Autonomous City Transport)[8] for the US DARPA Grand Challenge 2007 [18]. As can be seen in Figure 5 the vehicle included sensors ranging from GPS and inertial navigation to cameras, radar and laser range finders.

2.3 The Role of Smartphones as Driver for Continuous PNT

Almost three billion mobile applications currently in use rely on positioning information. In the recent GNSS market report, issue 4, 2015, from the European GNSS Agency[9] it is reported that GNSS is used around the globe, with almost four billion GNSS devices in use in 2014. By 2019, this is forecasted to increase to over seven billion – for an average of one device per person on the planet. Although there is significant regional variation in the world in GNSS penetration in terms of devices per capita, the up-take of smartphones in emerging regions will change the situation in almost every corner of the world. As a result, the 'digital divide' is forecasted to narrow. Smartphones continue to dominate (around three billion in 2014), being the most popular platform to access LBS, followed by devices used for road applications (0.26 billion). It is forecasted that the market for smartphones will grow by 6.2% per year through 2023. Other devices may be less numerous, but billions of passengers, professionals, consumers and citizens worldwide benefit from their application in efficient and safe transport networks, in productive and sustainable agriculture, surveying, and critical infrastructures.

These statistics prove notable that navigation services and LBS on smartphones have become very popular Hence, the characteristics (i. e. accuracy, limitations and potential) of modern low-cost, mass-market user sensors in smartphones for vehicle location in narrow / deep urban

8 http://archive.darpa.mil/grandchallenge/Teams/osu_act.html

9 http://www.gsa.europa.eu/2015-gnss-market-report

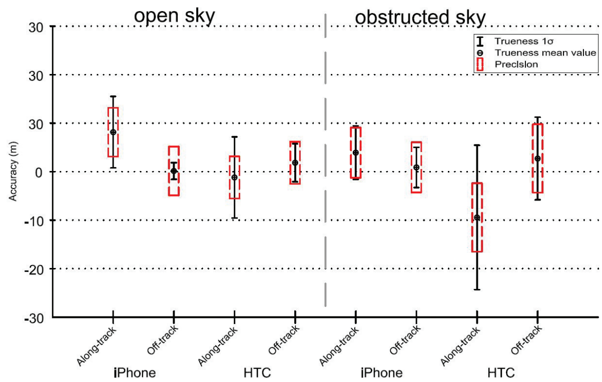

Figure 6: Estimated mean value and standard deviation of positioning trueness and smartphone reported precision values [8].

canyons and in partly indoor environments is briefly discussed. Figure 6 shows the position test statistics (precision and accuracy) for two contemporary smartphones obtained under open sky (on the left) and obstructed sky (on the right) environment in the along-track and off-track directions. The precision is a position quality figure reported directly from the smartphone navigation sensors and shows the measurement repeatability or reproducibility, whereas accuracy expresses the proximity of the navigation solution to the actual ("true") trajectory realized by a rigorously defined reference trajectory, which in this case was obtained using a high-end GNSS / IMU (NovAtel SPAN) system. Moreover, the along-track error represents the error in the direction of movement between the computed position and the ground truth whereas the off-track error reflects the lateral offset of the computed position from the reference travel path. The analysis of the GNSS data indicates that the overall positioning performance of the smartphones relates to the driving environment. An analysis of the vehicle location statistics reveals a deterioration in the standard deviation of accuracy and the precision mean by around 75 % and 30 % respectively in the deeply obscured environment compared to the open sky scenarios, whereas the along-track statistics exhibit marginally higher values compared to the off-track ones. Further analysis of the corresponding error time series revealed that the precision values obtained for the first smartphone (iPhone 5S) tend to be more stable than those for the second one (HTC One S) which might associated with differences in the data filtering procedures applied by their manufactures [8].

As expected, the smartphone tests show, remarkably, that in the GNSS navigation gap the performance degrades quickly, especially prior to entering indoor environments. Thus, using the traditional GNSS receiver approach, individual or all users in the area may be denied the ability to navigate. However, in a number of situations, groups (or networks) of GPS users may operate together using useful satellite signal information combined together from multiple users. The multi-sensory approach has then been further extended by the concept of CP [18]. In the following section the CP concept is discussed in more detail.

3 Collaborative Navigation Concept

A paradigm shift in the navigation solution has been observed in recent years. It has been manifested by an evolution from a traditional single sensor-based solution, to a multiple sensor-based solution, and now to collaborative navigation and layered sensing, often using unconventional sensors and techniques. This development follows-on from the multisensor navigation approach where GNSS augmentation was provided for each individual user by such sensors as IMUs, barometers, magnetometers, odometers, or digital compasses for applications ranging from pedestrian navigation, to georeferencing of remote sensing sensors in land-based and airborne platforms (see e. g. [4, 9, 10, 12, 13, 31, 34, 37, 41, 42]).

3.1 Operational Principle of CP

Collectively, a network of GNSS users (hereafter referred to as nodes) may be able to receive sufficient satellite signals, augmented by inter-nodal ranging measurements and other sensors, such as IMUs or active / passive imaging sensors, in order to form a joint position solution [15, 17, 18, 22, 25, 26, 46]. This network of GNSS 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 GNSS apertures.

Figure 7 illustrates the concept of CP in a dynamic network environment for emergency response and rescue. Sub-networks of nodes navigating jointly, can be created *ad-hoc*, as indicated by the circles in Figure 7. Some nodes may be part of different sub-networks. In a larger network, the selection of a sub-network of nodes is an important issue, as in case of a large number of users in the entire

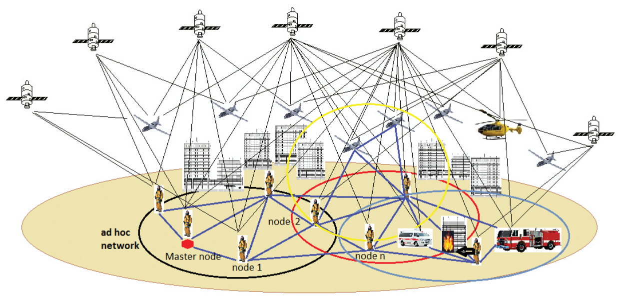

Figure 7: CP concept for emergency situations showing ground and combined ground/airborne *ad-hoc* networks.

network, computational and communication loads may not allow for the entire network to be treated as one entity. Still, information exchange among the sub-networks must be assured. Conceptually, the sub-networks can consist of nodes of equal hierarchy or may contain a master node (also called anchor node) that will normally have a better set of sensors and will be collecting measurements from all client nodes to perform the CP solution. It should be noted that the concept of a master node is also crucial from the standpoint of distributed GNSS aperture, where it is mandatory to have a master node responsible for combining all available GNSS signals. For more detail the reader is referred to [15].

The key components of a collaborative network system, illustrated in Figure 7, are the:

– Inter-nodal ranging sub-system (each user can be considered as a node of a dynamic network),
– Optimisation of dynamic network configuration,
– Time synchronisation,
– Optimum distributed GNSS aperture size for a given number of nodes,
– Communication sub-system,
– Selection of master or anchor nodes, and
– Network topology.

3.2 CP for ITS

In the context of C-ITS, the CP approach relies on information being shared between vehicles within a VANET, to overcome the limitations for positioning in the GNSS navigation gap. In this case, the information shared between vehicles can be in the form of inter-vehicle ranges, relative speed, orientation, and satellite related data. This is the case when all or some of the nodes (vehicles) are equipped with GPS. The network CP is done once the ranges and the position information are exchanged between the nodes. Sharing information could help the vehicles within the network to obtain positioning solutions even when the requirement of GNSS positioning cannot be met [25]. As an example, Figure 8 shows a possible positioning architecture for a VANET.

3.3 Sensors, Signals and Techniques

Different sensors and signals such as GNSS, UWB, WiFi, RFID, IMUs, MEMS-based accelerometers, gyroscopes, magnetometers, barometric pressure sensors, as well as optical

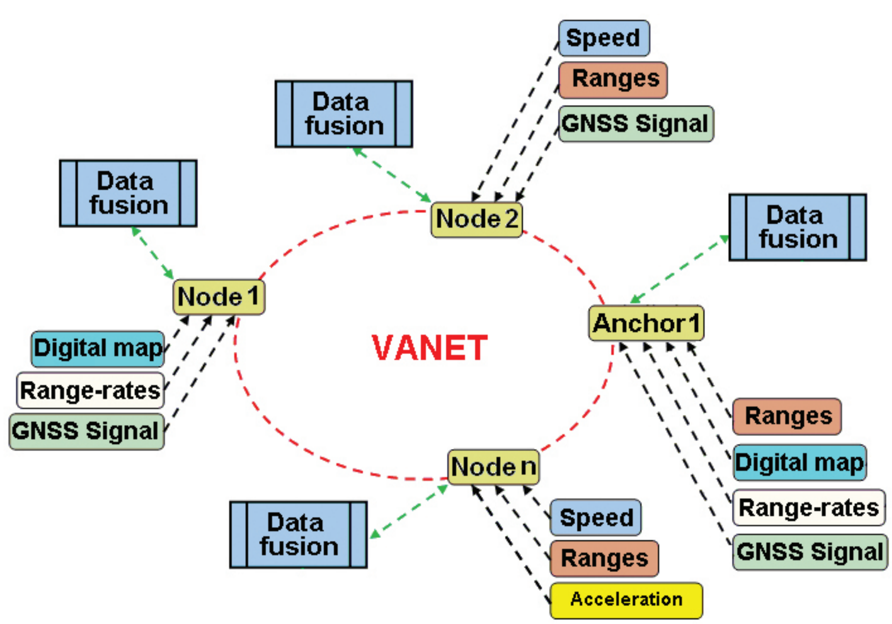

Figure 8: Example for a CP positioning architecture in a VANET [25].

systems and image-based sensors (i.e., digital cameras [19, 28], Flash LiDAR [38] and laser [39]) may be used in CP. Table 1 lists the most commonly used example sensors and techniques that can be used in collaborative navigation. Depending on the application additonal and newly emerging sensors / signals may be integrated. For a comprehensive compendium of currently available and deployable sensors the reader is referred to the paper [36] presented in a recent previous issue of this journal. Especially in connection with ubiquitous indoor localisation the trend is to integrate infrastructure-based systems (such as infrared or ultrasonic signals, UWB, RFID or other RF-based systems) with all available systems using so-called 'signals-of-opportunity' (i.e. RF signals not intended for positioning, for instance, WiFi, digital television, mobile telephony, FM radio and others) together with inertial navigation sensors. Commonly used sensors in a multi-sensor portable navigator, e.g., the personal navigator of the Ohio State University or the University of Nottingham (compare Table 3 or 4 for the detailed sensor specifications), include GNSS, IMU, magnetometer, barometer, step sensors (e.g. foot mounted), RF- and image-based ranging, etc. In general, a human location model is used to determine motion modes, such as running, walking, standing, etc., and aids navigation by distance travelled and direction estimation. The modeling, however, is quite complex and employs usually knowledge-based systems to infer information based on existing models and navigation status. Maps can be used to constrain position and heading. The key issue is the quality of georeferencing and data, including accuracy, spatial resolution, age of data, etc. A recent trend is the use of SLAM (Simultaneous Localization and Mapping) algorithms which are tailored to the available resources, hence at operational compliance. In the SLAM approach a map of an unknown environment is constructed or updated while simultaneously keeping track of an user's or other mobile platform's location within it. Popular approximate solution methods include the particle filter and extended Kalman filter (see section 3.4).

Table 1: Overview of most commonly used sensors for collaborative navigation [3, 10, 18, 19, 21, 27, 34, 35, 38, 39].

Type	Sensor	Navigation Information	Typical Accuracy	Characteristics
Radio Frequency (RF)	GNSS Position coordinates	X, Y, Z	~ 10 m (DGPS: 1–3 m)	Line-of-sight system Positions in global reference system
	Velocity	v_x, v_y v_z	~ 0.05 m / s ~ 0.2 m / s	
	Pseudolites (e. g. Locata)	X, Y, Z v_x, v_y, v_z	comparable to GNSS	Line-of-sight system GNSS or non-GNSS signals in the 1–2 GHz frequency band
	UWB	X, Y, Z	dm-level	Time-of-Arrival (ToA) and Angle-of-Arrival (AoA) Resistant to multipath fading Strong signal penetration Possible interference with GNSS
	WiFi	X, Y	1–3 m 2–6 m	for WiFi fingerprinting for WiFi signal strength-based Positions in a local frame Signal attenuation due to distance Penetration through walls Multipath affected Interference from other users in 2.4 GHz frequency band
	RFID	X, Y	depending on cell size 1–3 m	for RFID cell-based positioning for RFID Fingerprinting Different range for passive and active RFID tags
INS	Accelerometer	a_{tan}, a_{rad}, a_z	< 0.03 m / s^2	Subject to drift Calibration should be made when GPS is available

Table 1: (Continued)

Type	Sensor	Navigation Information	Typical Accuracy	Characteristics
INS	Gyroscope	heading φ	0.5°–3°	Short term accuracy stability Not subject to external disturbances but to drifts Calibration should be made when GPS is available
Optical Systems	2D image-based	α, β	0.01°–0.1°	Passive line-of-sight system
	Multi 2D image-based	X, Y, Z ω, ψ, κ	0.1 mm at image scale 0.01°–0.1°	Image overlap and conjugate points are required Scale is undefined
	3D image-based	X, Y, Z ω, ψ, κ	0.01–1 m 0.01°–0.1°	Active line-of-sight system Scale is known through ranging
	Optical sensor network	X, Y (Z optional)	few m	Image overlap required for 3D
	Laser	X, Y, Z	cm to dm	Local or global reference frame
Others	Digital compass / magnetometer	heading φ	0.5°–3°	Long-term accuracy stability Subject to magnetic disturbances Sensitive to tilt
	Barometric pressure sensor	Z	1–3 m	Requires calibration by a given initial height to provide heights with respect to a global reference frame
	Temperature sensor	T	0.2°–0.5° C	For barometric height conversion Specifications are for low-cost sensors, e. g. which are built-in in smartphones or other mobile devices
	Odometer	n	0.01–0.1 %	Long term stibilty Needs calibration
	Step sensor	n	2–20 %	Subject to human characteristics and motion mode Should be calibrated when reference (GNSS, etc.) is available

Figure 9 shows an example for a CP module consisting of a positioning device (GPS unit), communication and ranging device (Dedicated short-range communications DSRC), computational processor (Kalman Filter KF processing unit) and digital map [25].

Dedicated short-range communications (DSRC) is a wireless communication channel designed specifically to support V2V and V2I communications. In the U. S., the Federal Communication Commission (FCC) has allocated DSRC with a dedicated bandwidth of 75 MHz in the 5.850 to 5.925 GHz band, whereas the European Telecommunications Standards Institute (ETSI) has allocated a dedicated bandwidth of 30 MHz in the 5.9 GHz band. DSRC is able to provide low latency, high speed communication, and strong and relative close proximity signals [33], hence making it a suitable candidate for the enablement of CP techniques within a VANET. In fact, DSRC underpins plans in the US to develop telematics regulations that will require new cars and light trucks sold in the US to be equipped with systems for V2V communications. Raising concerns about privacy, the intention is for "vehicles equipped with DRSC chips to receive and process signals from nearby DRSC-enabled cars to learn their location, direction and speed. If a driver does not react to an impending collision, the car could then sound a warning or apply the brakes automatically to prevent an accident.[10]" Fundamentally, DSRC communications combined with

10 http://www.thetruthaboutcars.com/2014/02/u-s-dot-to-mandate-vehicle-to-vehicle-telematics-for-crash-avoidance-sparking-privacy-concerns/

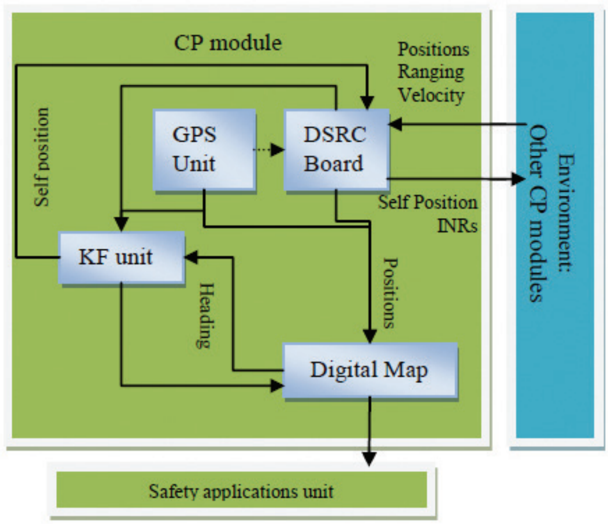

Figure 9: CP module consisting of positioning device (GPS unit), communication and ranging device (DSRC), computational processor (KF processing unit) and digital map [25].

a robust positioning capability and the core technologies are required to realise the significant benefits of C-ITS for road safety [25].

3.4 CP Integration Algorithms

Many different types of network configuration and sensor integration techniques are possible in CP (see e. g. [25, 41, 42]). Perhaps one of the most widely used algorithm is the Kalman Filter (KF). The KF is a recursive algorithm that uses a series of prediction and measurement update steps to obtain an optimal, in a minimum variance sense, estimate of the state vector. The KF algorithm can be categorized into the prediction and update groups. Essentially, the prediction group describes how the state vector and its covariance propagate through time, based on the current state and assumed system model. Then, the update group updates the Kalman Gain, state vector and system variance. The Kalman Gain, in a loose sense, weights the process and measurements accordingly, taking account of their respective variances. Then, using the Kalman Gain, the state vector is updated with new measurements. Finally, the system variance is updated, using both Kalman Gain and the *a priori* variance. The algorithm is then recursively applied to subsequent epochs. For non-linear systems, the Extended KF (EKF) is widely used where the process or measurement nonlinear models are linearized before implementing the KF. The integration of the sensor observations and inter-nodal range measurements is performed either with loose, tight or ultra-tight coupling. Hence, the collaborative navigation solution is formed by integrating the inter-nodal range measurements to other users or platforms. The advantage of using a tight coupling approach is that the inter-nodal range measurements directly are integrated to each node's local measurements in order to calibrate the IMU errors even during GNSS outages. To strengthen the final CP solution, single user GNSS observables may be enhanced using external information such that derived from a terrain model and an estimate of its uncertainty. Depending on CP node configuration, the integration level of such an approach may be applied at a pre-processing stage to blend GNSS pseudo-ranges with receiver elevation and some knowledge of at least way-point direction through pre-filtering or potentially may be fully embedded in the KF model at a CP network level.

Monte Carlo Localization (MCL), also known as particle filter (PF), is widely used for robot localization in an indoor environment where it uses fast sampling technique to represent the robot's belief. As presented in [6], the MCL algorithm is summarized as: starting with a prediction phase, a set of particles S_{k-1} is sampled. Then each set is applied through a motion model by sampling $P(x_k|s^i_{k-1}, u_{k-1})$. This results in a new set of S'_k, which approximates a random sample from the predictive density $P(x_k|z^{k-1})$. Next, the update phase is applied where measurements z_k are taken into account to weigh all of the sampling sets, which is given by $m^i_k = p(z_k|s'^i_k)$. Then S_k is computed by re-sampling from the weighted set. These two phases are repeated recursively for the subsequent steps. The MCL has some advantages over the other algorithms such as, unlike KF, MCL is able to represent multi-modal distributions, which is useful for self-localization and it is relatively easy to implement (see [24]). The MCL algorithm is not only limited to robot localization, but extends to wireless sensor networks (WSN) as shown in [43].

Another algorithm used for WSN localization is the SPAWN algorithm. The SPAWN algorithm makes use of factor graphs (FG) and sum product algorithm (SPA) where the FG is a method of graphically represent a factorization of a Bayesian network while the SPA is a message passing algorithm for performing inference on the FG. Consider a WSN consisting a set of nodes and a set of anchors. Each node elaborates its information from the previous step from its last position estimation. Then it receives messages from visible anchors and neighbouring nodes. Using the new information, it updates its positional estimation and shares it with its neighbours. The messages shared among the nodes represent a probability density function. This makes the approach a truly distributed algorithm which is highly suitable for CP [44].

4 Nottingham Field Trials

The CP concept is investigated and validated based on field test data collected in a campaign at the University of Nottingham in one week of May 2012. A network of five kinematic platforms were employed in the field trials, i. e., a roof top train on the Nottingham Geospatial Building (NGB), two mobile mapping vans, and two personal navigators from the Ohio State University (OSU) and the University of Nottingham. A sample of the platforms used in the experiments are shown in Figure 10.

The train on the roof of the NGB was equipped with a Novatel GPS, a tactical grade Novatel SPAN IMU, and two MEMS-based IMU's, i. e., the Xsens MTi-G and the Systron Donner Inertial MMQG, and an Omnisense UWB receiver in some of the tests. The sensor specifications are given in Table 2. The personal navigator from the Ohio State University OSU consists of the sensors listed in Table 3. In addition, an Xsens MTi IMU, either an Omnisense or Thales UWB receiver and a tracking prism have been mounted on the personal navigator in some of the tests. The personal navigator from the University of Nottingham includes the sensors given in Table 4. Also, an Xsens MTi-G and an UWB receiver (Omnisense or Thales) was carried with the personal navigator. The two mobile mapping vans were equipped with the sensors described in Table 5 and 6. Using DSRC the distances between the vehicles can be estimated by radio ranging for their positioning solutions besides sharing information among vehicles (see e. g. [1, 7]). The specifications of the DSRC transceivers can be found in Table 7.

Figure 10: Impressions from the Nottingham field experiments showing Charles Toth with the personal navigator from the Ohio State University (left), Dorota Grejner-Brzezinska with the personal navigator of the University of Nottingham (middle) and the roof top train on the Nottingham Geospatial Building (right).

Table 2: Sensor Specifications of the roof top train.

SENSOR	INTERFACE	DATA RATE	GPS TIMETAGGING	RECORDING
Novatel GPS	USB	10 Hz	yes	Internal
SPAN HG1700 IMU	COM / USB	100 Hz	GPSCard	Laptop
Xsens MTi-G	USB	100 Hz	yes	Laptop
Systron Donner Inertial MMQG	USB	100 Hz	yes	Laptop

Table 3: Sensor Specifications of the personal navigator of the Ohio State University.

SENSOR	INTERFACE	DATA RATE	GPS TIMETAGGING	RECORDING
SPAN on OEMV3	COM / USB	50 Hz	n / a	Laptop II
iMAR FSAS IMU	COM / USB	200 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

Table 3: (Continued)

SENSOR	INTERFACE	DATA RATE	GPS TIMETAGGING	RECORDING
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 4: Sensor Specifications of the personal navigator of the University of Nottingham.

SENSOR	INTERFACE	DATA RATE	GPS TIMETAGGING	RECORDING
Microstrain 3DM-GX3-25	Serial	100 Hz	no[11]	PTDL[12]
Xsens MTi-G	USB	100 Hz	no[11]	Laptop
Leica GS10 with AS10 antenna	n / a	10 Hz	n / a	Internal
u-blox ANTARIS 4	Serial	10 Hz	n / a	PTDL[12]

Table 5: Sensor Specifications of the mobile mapping van 1.

SENSOR	INTERFACE	DATA RATE	GPS TIMETAGGING	RECORDING
SPAN HG1700 IMU	COM / USB	100 Hz	GPSCard	Laptop
DSRC Transceiver	USB	10 Hz	yes	Internal / external (laptop)
Xsens MTi-G	USB	100 Hz	yes	Laptop
Systron Donner Inertial MMQG	USB	100 Hz	yes	Laptop

Table 6: Sensor Specifications of the mobile mapping van 2.

SENSOR	INTERFACE	DATA RATE	GPS TIMETAGGING	RECORDING
Leica GS10 with AS10 antenna	n / a	10 Hz	n / a	Internal
CIMU	COM / USB	100 Hz	yes	Internal
DSRC Transceiver	USB	10 Hz	yes	Internal / external (laptop)
Xsens MTi-G	USB	100 Hz	yes	Laptop
Systron Donner Inertial MMQG	USB	100 Hz	Yes	Laptop

Different test scenarios with different mobile platforms in combined indoor / outdoor environments have been performed. Several scenarios on the roof of the NGB tested the use of the sensors on the train in conjunction with the personal navigators. In these tests the train moves along a known reference track in the shape of a figure of 8. The persons with the personal navigators partly followed the moving train or were walking in front of the train either in the same or different directions. In some of the tests also an UWB receiver from Omnisense was carried by the persons with the personal navigators, another one was mounted on the train and a fourth receiver was stationary. Apart from the movement on the building roof the persons with the personal navigators 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 for checking. The path outside the building

11 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.

12 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 7: Specifications of the DSRC 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)

led through parts of the Jubilee Campus of the University of Nottingham passing by several other buildings. Along the outdoor path the GNSS availability varied significantly.

In a dedicated indoor test the positioning capabilities of the personal navigators inside the building was investigated. For that purpose six 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 navigators. In addition, a Leica total station was positioned on the ground floor near the building entrance for tracking of the personal navigators (which were 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 outdoors to be able to receive GNSS signals.

In the tests with two mobile mapping vans the personal navigators moved around the car park in front of the Nottingham Geospatial Building. The persons with the personal navigators finally went also inside the building

Figure 11: Two mobile mapping vans equipped with GNSS receivers, inertial sensors and DSRC transceivers.

at the end of this test. In addition, the mobile mapping vans were driven on road sections of the A52 Clifton Blvd. near the university campus to test the DSRC performance. Figure 11 shows the two mobile mapping vans equipped with the sensors listed in Table 5 and 6.

First results of these experiments are presented in the papers [22–24]. They indicate that CP is capable of providing significant navigation improvements, as well as enabling navigation in otherwise challenging environments. The most important aspect is the continuity and availability of the navigation solution, particularly in the transition environments. Sub-meter to a few-meter level of accuracy can be achieved indoors and in transition environments, if image-based navigation is properly integrated with the IMU-supplied navigation information, using (1) tight integration (compare section 3) and (2) sensor calibration using GNSS signals during the clear line-of-sight navigation period [18].

The observation data of the Nottingham experiments has been made available online for interested researchers. Further information can be found at http://ubpos.net/. In the following section selected test results are presented and discussed.

5 Selected Field Experiment Test Results

In this section selected results from the Nottingham trials are presented. Firstly, a brief summary about the performance of the personal navigator of the Ohio State University is given, followed by an investigation of the use of UWB with the personal navigators. Then an approach called 'Terrain-Aiding' for GNSS pseudo-range data is discussed. To conclude this section tests with the two mobile mapping vans are described showing the performance of CP under different GNSS satellite visibility conditions and partial outages.

5.1 OSU Personal Navigator Performance

Interest in personal navigation (PN) has been rapidly growing as advancements in sensor miniaturization and integration make the technology increasingly affordable. PN, in particular, is important in indoors, as in open-sky environment GNSS can provide adequate navigation performance. The OSU SPIN Lab has been involved in PN research for about a decade, with a primary focus on human motion modeling, using Artificial Intelligence (AI) techniques, image-based and collaborative navigation topics. PN navigation represents a rather different scenario compared to other platforms, such as aircraft and land vehicle navigation, as due to the slower motion the attitude can vary over a broad range; people can move sideways, turn rapidly, etc. This means that the classical trajectory estimation methods, which are mostly based on Extended Kalman-filter (EKF) solution, cannot be directly applied to PN navigation because of the high nonlinearity of motion model. Therefore, non-physical model-based approaches are considered, such as neural networks or Fuzzy logic that try to correlate the sensory data to the trajectory in a general way. In both cases, knowledge must be acquired in typical situations before the method actually can be applied to PN navigation (see [11, 29]). In addition, neural network may be combined with EKF for PN integrity monitoring (see [30]). Modeling the human motion can provide essential information to the trajectory estimation process, as it may narrow down estimation space, resulting in faster and more reliable solutions. For example, sensing footsteps and combining it with other sensory data can effectively support dead-reckoning and attitude estimation [14].

Image based navigation has been around for a long while, and was originally applied to airborne platforms; first based on optical imagery, and more recently laser-scanning too (see [2]). Imaging sensors are particularly advantageous for PN, as they can effectively map the area around the platform and may provide information beyond navigation, such as obstacle avoidance or monitoring other moving objects in the vicinity (see [20]). More recently, 3D or depth cameras (RGB-D) have become widely available, providing direct 3D observation of the object space, resulting in more robust solutions in most scenarios (see [40]). More importantly, the availability of imaging sensors is supported with powerful computer vision techniques, such as dense point matching, including point cloud generation based on imagery and point cloud matching. In favorable conditions, such as not too complex object space with good texture and depth information image based navigation could be quite accurate, reaching a few cm relative positioning accuracy. The Nottingham Field Trial was an important milestone in PN performance validation, as it provided a very controlled environment. The building inside had several reference point, the blueprint of the structure was available, and a robotic total station tracked to PN. In addition, UWB sensors were also used in the testing, to advance collaborative navigation research, two PN platforms acquired data. The performance evaluation has confirmed that cm and dm-level accuracy can be achieved for different segments of the PN trajectory; an intermittent time synchronization error prevented to reconstruction of the entire PN trajectories. Since the Nottingham test, smartphone have shown remarkable development in sensor performance and are becoming a generic platform for indoor PN navigation; obviously, they have been already used for PN outdoors.

5.2 Investigation of UWB Usage

As already stated, an UWB system by Omnisense was tested in conjunction with the rest of the equipment. The UWB system consisted of four sensors; a stationery master (node #20), and three additional roving nodes; one placed on the OSU personal navigator (node #26), one on the NGI personal navigator (#27) and the last one onboard the NGB roof top train (#21). Data acquisition was carried out by logging raw data from the master station. The output of the UWB sensors was delivered in three different custom formats (JSON, NMEA-like sentences, and a specific Estimated Position sentence type) and included observables from the embedded accelerometers, gyroscopes, range finders and GPS sensors. Specific software was written in C# WPF to analyze the output and to visualize the positioning solution as computed by the system. (In total, 3861 sentences were recorded, corresponding to a time span of approximately 16 minutes.) Unfortunately, issues related to the overall configuration and logging setup strategy deprived further processing from being carried out. The main reason behind this pitfall was the inability to correlate the UWB observables with the collected data from the other sensors onboard the platforms. Despite the unfavourable results obtained in this test, the potential of UWB technology as a complement to other systems for PNT applications is high due to its precision peer-to-peer ranging, radar sensing and communication capabilities. Currently, further testing is undertaken by the authors using other UWB systems in variant operating environments and in combination with other sensor types.

5.3 Test of Terrain-Aiding for GNSS Positioning

At a preliminary stage, in order to investigate the potential of processing GNSS pseudo-range data in conjunction with a terrain model a new formulation of the standard height-aiding algorithm, named Terrain-Aiding (TA) [5] was tested. In this approach an approximate position is used to look up a height which provides a loose constraint to get a more accurate position and so a more accurate height from the terrain model, whereas the process continues iteratively until convergence is reached.

Notably, due to the relatively flatness of the trajectories and the entire lack of satellites in the building area, the Nottingham data cannot take full advantage of the technique. However, as an example, we simulated (artificially decimated) the GNSS observations collected with the OSU personal navigator for part of the outdoor test passing by the Nottingham Geospatial Building to obtain the best possible conditions for testing the algorithm. In one of the trials, the original data were decimated to epochs consisting only three satellites resulting to 25822 combinations of satellite triplets and subsequently the TA algorithm was applied using a constant receiver height value. Figure 12 shows the frequency distribution and statistics of the 2D error; namely, the deviation in the receiver horizontal position obtained between the TA solution and

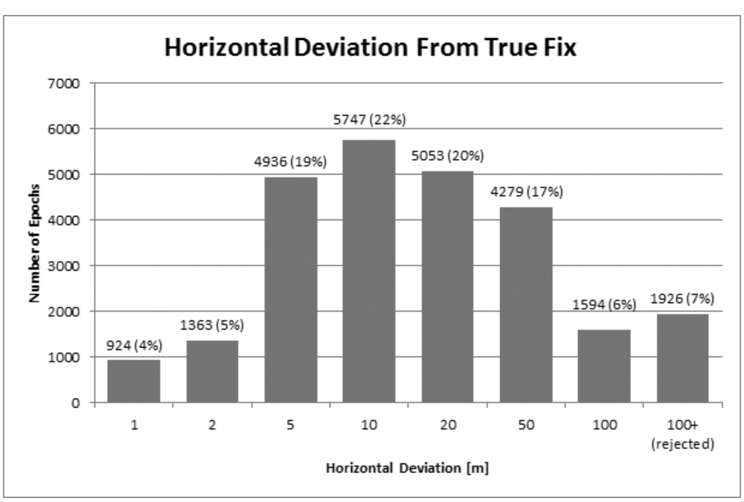

Figure 12: Deviation in GNSS receiver horizontal position obtained between the "terrain-aided" and standard GNSS/INS solution.

that of the integrated GNSS/INS one. From these results it appears that a use of the TA approach for stand-alone GNSS positioning may render ill-conditioned GNSS epochs to "usable" locations, whereas its potential may further be enhanced through its integration within a GNSS / IMU KF processing scheme.

5.4 Mobile Mapping Vans Test Results

This test aims to evaluate the effectiveness of a proposed CP approach where GNSS / IMU and inter-vehicular ranges are used to improve positioning outputs, without the use of radio based ranging. The participating vehicles exchange pseudo-ranges, positions and their respective variances and the medium of which they are exchanged is by utilizing the DSRC as depicted in Figure 13. In each vehicle, the integration engine makes use of the inertial measurements acceleration and turning rate (f_v, ω_v) from its IMU, pseudo-ranges (ρ_v) from its GNSS receiver, pseudo-ranges and position from the neighbouring vehicle via DSRC. The EKF is chosen as the integration estimator where all of these measurements are used to provide positioning output, i. e. position, velocity and orientation (r_v, v_v, θ_v).

The proposed CP approach was compared against a conventional GNSS / IMU integrated system, under the influence of signal shadowing effects, or better known as GNSS outage. Here, one vehicle acts as the aiding source, while the other receives information through its DSRC, termed as the target vehicle. Two scenarios are considered in this test to reflect a typical urban environment; performance with partial GNSS with only three and two satellites available. To observe its performance further, the duration of the simulated GNSS outages was varied from 60, 180 to 300 seconds. The results will be presented as root mean squared error (RMSE), maximum error and RMSE percentage of improvement.

Before presenting the results of the CP method with partial GNSS availability, it is worth noting that the proposed method does not provide any real performance gain when full GNSS are available (more than three pseudoranges), where the 2D RMSE is around 1.555 m. The following paragraphs details the performance of the proposed CP during partial GNSS outages. It will first present the result when only three satellites are available, followed by two satellites are available, where the duration of partial outages are varied to 60, 180 and 300 seconds.

As seen in Figure 14 and Table 8, the performance of CP has improved significantly when only three satellites are available for the target vehicle. Its 2D RMSE improved by 60 % and 50 % when experiencing 60 and 300 seconds of partial outages respectively. On the other hand, CP with three satellites 3D RMSE only improved slightly. For example, the CP RMSE improved over GNSS / IMU by 6 % and 2 % during the 60 and 300 seconds outages respectively. The CP maximum error shows similar pattern to its RMSE where its 2D maximum error has improved more than its 3D maximum error. Not all of the CP results improved over GNSS / IMU, for example, CP maximum error when experiencing 300 seconds of partial outage is higher than its GNSS / IMU

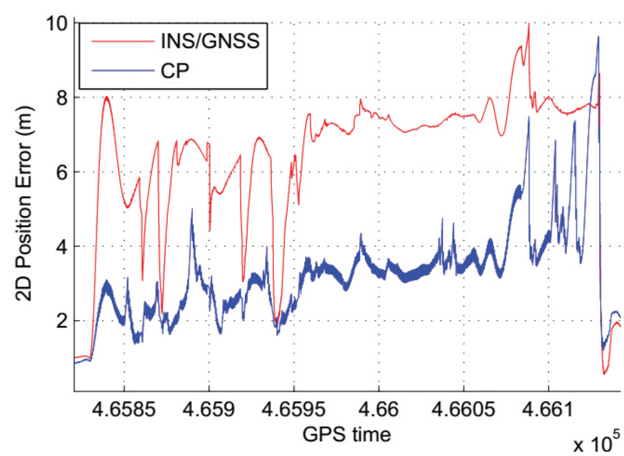

Figure 14: Position error for 3 satellites, 300 seconds outage.

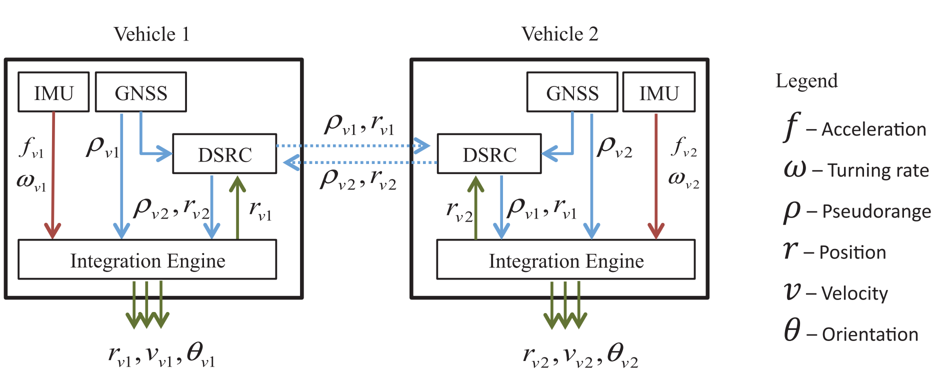

Figure 13: Schematic of the proposed TC CP approach.

counterpart. The difference was observed at the later part of the simulated outage and is due to the effect of positioning errors from the aiding vehicle.

Similar to when three satellites are available, the 2D results in the two satellites scenario show that CP has improved performance compared to GNSS / IMU only (compare Figure 15 and Table 9). The percentage of improvements are 40 %, 43 % and 24 % for 60, 180 and 300 seconds of outages. On the other hand, its 3D performance decreased by 25 % or 2 m than its counterpart when experiencing 300 seconds of outage. The results for CP maximum errors are also similar to RMSE where for most part, are significantly better than GNSS / IMU. For example, during 60 seconds of partial outage, the maximum error observed is reduced by 39 % when compared to GNSS / IMU.

Table 8: Partial GNSS, 3 satellites RMSE and Max Error

3 satellites	RMSE [m]		Max Error [m]	
60 seconds	2D	3D	2D	3D
GNSS/IMU	5.661	9.988	8.029	12.613
CP	2.233	9.384	5.007	10.580
Improvement [%]	60.548	6.043	37.646	16.115
180 seconds	2D	3D	2D	3D
GNSS/IMU	6.128	8.997	8.029	13.583
CP	2.731	8.826	5.013	11.381
Improvement [%]	55.433	1.897	37.560	16.209
300 seconds	2D	3D	2D	3D
GNSS/IMU	6.744	9.078	9.999	13.583
CP	3.360	8.889	9.635	15.979
Improvement [%]	50.179	2.077	3.640	−17.644

When comparing the two scenarios of CP performance in terms of RMSE during partial GNSS outages, it can be seen that its performance degrades over time. This indicates that although CP uses aiding ranging from other vehicles, its performance is heavily reliant on the performance of the IMU, where as numerous studies have shown that its performance also degrades over time. Also, the performance of CP is dependent on the quality of the aiding vehicle's position information. Hence, if the quality of the vehicles position is poor, naturally it will affect the quality of the aided vehicle. Nonetheless, the proposed CP approach has shown significant improvements particularly its 2D solutions when GNSS is only partially available. This would be beneficial for applications requiring critical positioning in GNSS hostile environments.

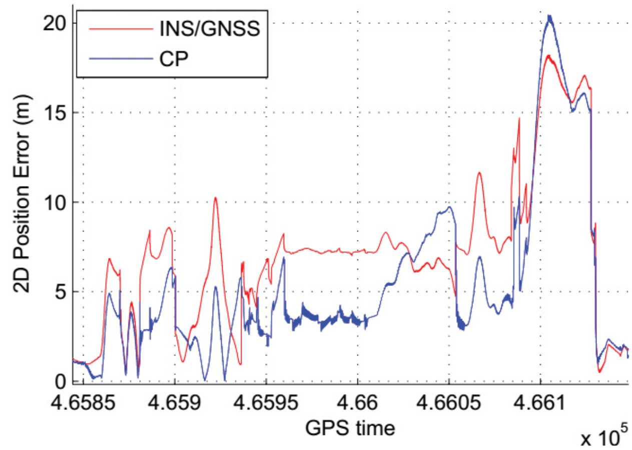

Figure 15: Position error for 2 satellites, 300 seconds outage.

Table 9: Partial GNSS, 2 satellites RMSE and Max Error.

2 satellites	RMSE [m]		Max Error [m]	
60 seconds	2D	3D	2D	3D
GNSS / IMU	3.143	9.369	8.447	10.937
CP	1.873	9.499	5.091	10.341
Improvement [%]	40.414	−1.390	39.737	5.451
180 seconds				
GNSS / IMU	5.121	8.797	10.271	12.044
CP	2.888	9.786	6.944	13.499
Improvement [%]	43.609	−11.242	32.399	−12.080
300 seconds				
GNSS / IMU	7.157	9.488	18.219	18.744
CP	5.401	11.917	20.463	21.375
Improvement [%]	24.529	−25.592	−12.315	−14.036

6 Concluding Remarks and Outlook

Current CP initiatives undertaken by a joint working group, consisting of FIG Commission 5 and IAG Commission 4 have been presented. The group has also investigated innovative algorithms and DSRC communication methods to enhance CP performance in terms of positioning accuracy and availability on different mobile platforms. A significant experimental field campaign and subsequent processing and analysis between 2012–2015 has demonstrated that CP improves positioning and navigation information for all users, in terms of accuracy, integrity, availability and continuity – particularly during gaps in the GNSS coverage. Finally, the paper discussed some of the challenges for further improving of CP capabilities, which will be the focus of the group's future work. Suitable sensors and processing approaches identified in this phase of work will be topics of further investigation by the group, with further field trials are planned in the near future. Interested researchers can download the experimental test data freely from http://ubpos.net/ and are invited by the authors to join the work of the group.

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