Combining visual, pedestrian, and collaborative navigation techniques for team based infrastructure free indoor navigation

Aiden J. Morrison[1], Laura Ruotsalainen[2,3], Maija Makela[2], Jesperi Rantanen[2], Nadezda Sokolova[1],
SINTEF[1], FGI[2], University of Helsinki[3]

BIOGRAPHIES

Aiden Morrison received his PhD degree in 2010 from the University of Calgary. Currently, he works as a research scientist at SINTEF Digital. His main research interests are in the areas of GNSS and multi-user collaborative navigation systems.

Laura Ruotsalainen received her PhD in pervasive computing from Tampere University of Technology in 2013, and currently works as an associate professor at the University of Helsinki and as a part-time research professor at the Finnish Geospatial Research Institute.

Maija Mäkelä received her MSc in Science and Engineering from the Tampere University of Technology in 2016 and is now pursuing a doctoral degree in the same university. She currently works as a research scientist in the Finnish Geospatial Research Institute, focusing on collaborative navigation methods and algorithms.

Jesperi Rantanen received his M.Sc. (Tech.) degree in Geomatics from Aalto University School of Engineering, Finland, in 2015 and he is currently pursuing a doctoral degree at the University of Tampere. He works as a researcher at the Finnish Geospatial Research Institute focusing on developing adaptive navigation systems.

Nadezda Sokolova received her PhD degree in 2011 from Norwegian University of Science and Technology (NTNU), where she worked on weak GNSS signal tracking and use of GNSS for precise velocity and acceleration determination. Currently, she works as a research scientist at SINTEF Digital, and adjunct associate professor at the Engineering Cybernetics Department, NTNU focusing on GNSS integrity monitoring and multi-sensor navigation.

ABSTRACT

In this paper the authors describe the design and evaluation of a multi sensor integrated navigation system specifically targeted at teams of cooperating users operating in transient indoor conditions such as would be encountered by emergency services personnel or soldiers entering unknown buildings. Since these conditions preclude the use of dedicated indoor infrastructure the system depends on the combination of multiple self contained navigation sensors as well as dynamic networking and ranging between the users to form a decentralized cooperative navigating team. Within this paper we will discuss the design and evaluation of a system developed within a North Atlantic Treaty Organization (NATO) Science for Peace and Security (SPS) project executed by the SINTEF and the Finnish Geospatial Researcher Institute (FGI) during 2018 and 2019. The motivation of this project was to combine the expertise of the FGI in pedestrian and camera based infrastructure free navigation with the collaborative navigation and integrated navigation system design expertise of SINTEF towards the accurate navigation and continuous situational awareness of teams of cooperating users. When completed, the combined navigation system will be a shoulder mounted package which comprises a triple frequency GNSS receiver for rapid outdoor initialization, as well as a Micro Electro Mechanical System (MEMS) Inertial Measurement Unit (IMU), barometer, magnetometer, three different navigation and communication radios as well as a stereo vision plus depth sensing camera connected to and synchronized by an integrated processor platform. Two of the three radios provide for user-to-user range measurement and data exchange via each of 2.4 GHz and Ultra Wide-Band (UWB) signals to allow for collaborative navigation as well as situational awareness within the network, while the 3rd radio provides a link to separate navigation sensors such as a foot mounted IMU pod for enhanced Pedestrian Dead Reckoning (PDR). The integrated camera provides

stereo color imaging as well as structured light based infrared depth sensing, while the processor platform is responsible for data collection and processing.

Introduction

The motivation in pursuing infrastructure free navigation systems relates to the fact that certain classes of user including fire-fighters, law enforcement, soldiers and others must enter hazardous indoor environments on short notice and without detailed knowledge of the interior structure, layout or contents of these buildings. Additionally, since the building might be on fire or otherwise denied electrical power, reliance on even ad-hoc infrastructure such as Wi-Fi routers may not be a reliable source of navigation data. Assuming that the building materials block the majority of GNSS signals to the users, the remaining options are typically those sources of information that are self-contained to the individual user such as inertial sensors and visual odometry (VO) to allow each user to navigate free of infrastructure, as well as leveraging the collective network via user to user radio links to realize collaborative navigation within the team.

Background

The Infrastructure-free tactical situational awareness (INTACT) project, funded by the Finnish Scientific Advisory Board for Defence (MATINE) for years 2015-2017, analyzed and developed methods for infrastructure–free simultaneous localization and mapping (SLAM) and context recognition for tactical situational awareness using only measurements obtained from small and low-cost MEMS sensors mounted on the body of the user. More precisely, during the project error analysis, and estimation methods were developed for obtaining accurate and reliable horizontal position solution fusing measurements from inertial sensors and computer vision and vertical position solution from fusing barometer and sonar observations [1]. Machine learning was used for detecting the user motion and thereby adjusting the estimation parameters and thresholds for improved solution [2]. At the end of the project a proof-of-concept was carried out at the military premises in Finland by two soldiers. Computation of the fused navigation solution was complicated by exposing inertial sensors and the camera to atypical motion and harsh impacts, such as jumps, running and climbing stall bars sideways. The final result, accuracy being 1% of the travelled path, was analyzed to be comparable with state-of-the-art infrastructure-free navigation solutions made by walking forward along a largely straight path [3].

SINTEF had previously conducted multiple projects exploring the feasibility of team based navigation in outdoor-indoor building entry scenarios, and through work funded by the Norwegian Battle Lab and Experimentation (NOBLE), prototype shoulder mounted navigation systems comprising GNSS, inertial and dual user-to-user range estimating radio modules which allowed direct implementation and testing of the collaborative navigation concepts explained in the next subsection. In these initial studies the navigation performance of each individual user was enhanced, relative user to user error was reduced, and the situational awareness of the overall team status was greatly enhanced through the periodic forwarding of 3rd party user status when performing ranging cycles, allowing a hypothetical supervisor or vehicle mounted node outside the building to serve as both a reference anchor for ranging but also to maintain knowledge of the entire team even when Line-of-Sight (LOS) communication was blocked to most team members.

While the INTACT project and collaborative navigation projects both achieved respectable performance during their respective testing, the individual systems had notable drawbacks, such as requiring illumination within the environment to be relatively high for proper operation of the visual odometry within the INTACT system, and the long term systemic drift of the collaborative navigation systems when the entire team was isolated from absolute position reference for an extended period of time. Before moving further, a more detailed explanation of the techniques that are to be combined in this study are now presented.

CORE TECHNIQUES

The combined SINTEF FGI navigation system, and the tests conducted in this study rely on several sources of navigation data throughout a typical outdoor-indoor trajectory. While GNSS is only used during system initialization, and barometry provides only a height constraint, the primary sources of Position Velocity and Attitude (PVA) estimation are derived from Collaborative Navigation, VO, and PDR, the implementations of which are now discussed.

Collaborative Navigation

Collaborative navigation is based on an idea of using team members as local beacons. By measuring distance to other team members and utilizing those measurements along with shared location information, the navigation solution can be enhanced especially in GNSS-challenged environments. Collaborative navigation approaches can provide position estimate in a global coordinate frame also to team members without access to GNSS signals, given that at least some team members are able to use satellite navigation [4]. Even if the whole team has no GNSS signal available, as can happen for instance in indoor environments, they can estimate their absolute and relative positions using the range constraints along with the estimates formed by their inertial navigation sensors.

The position estimation algorithm in collaborative navigation can be either centralized or de-centralized [5]. In the centralized approach, all measurements made by the team members are transmitted to some central processing unit. The unit computes the position estimates and transmits them back to the collaborators. In de-centralized approach each team member uses only measurements made locally, and position plus range estimates broadcast by other team members which can be directly communicated with. Compared to centralized position estimation, the de-centralized approach requires less communications over the network, scales better with the size of the team [5][6], and is tolerant of extended gaps in communication between individuals or groups of users.

The key element in collaborative navigation is distance measurements between the team members. UWB ranging suits well for the application at hand, as it is tolerant to multipath and can also be used through walls up to some extent [7]. However, this can make sensor fusion more challenging as in Non-Line-of-Sight (NLOS) situations the UWB distance measurement error is not necessarily Gaussian [8], which is a requirement for Extended Kalman Filter (EKF) [9] commonly used in navigation applications. Overbounding Gaussian distributions can be used in the EKF but this approach does not necessarily provide optimal results [10]. Without GNSS clock synchronization between the ranging devices can be difficult to maintain, but by using Two-Way Time-of-Arrival (TOA) distance measurements or synchronizing a sufficiently stable local oscillator when GNSS is available the requirement of clock synchronization can be avoided.

In this project, a completely de-centralized implementation is adopted as the target environments are those where point to point communication will be unreliable, and therefore centralized processing of data with reasonable latency is not considered feasible. In this de-centralized implementation users periodically announce their presence to other users in range, who keep an updated list of which users are recently visible and therefore considered valid targets for ranging and communication. Multiple-access for up to 32 nodes is achieved through time slicing based on user addresses, with synchronization of the mobile nodes to a common time base achieved via use of the onboard GNSS receiver during initialization, and carried forward by a local oscillator with stability sufficient to maintain valid access patterns for over 30 minutes without further GNSS updates. During an individual users' active time slice, they begin by transmitting a beacon frame to announce their presence to other nodes then execute up to five ranging cycles to other users if their list of visible users contains at least five other recently seen users. When more than five other users are known to be nearby the ranging cycles proceed in a least-recently-served sequence. A ranging cycle is divided in to four sub-cycles in order to exchange sufficient timing data to allow TOF between the two users to be calculated by the targeted user, and to communicate this calculated range back to the initiating user per [11][12]. During the sub-cycles the users exchange information on their current position estimates and the estimated uncertainty in their position estimates, to allow each user to use the measured range as a one-dimensional constraint during their local filter update. Additionally during the ranging sub-cycles two copies of 3rd party user data are exchanged when available to allow status updates about users to propagate through the network even when ranging data to these users is not available. This latter feature is used to provide situational awareness to each individual user even if their indoor position breaks most of their direct connections to other cooperating users, so long as at least one common path remains. In past tests of this capability it was shown to provide situational awareness to an isolated user of approximately once per several seconds, even in a challenging test environment.

Visual Odometry

Visual odometry determines the motion of a camera, namely the translation and change in orientation between two consecutive images by tracking the change in the location of image features representing the same real world object. Resolving the orientation change is straightforward, but detection of the mono-camera translation accurately is challenging, because it may be solved only within an ambiguous scale without having some additional information, such as size of the objects in the scene [13], or motion information obtained using other means. We wanted the visual perception to remain as an independent source of motion and therefore used a special configuration of the camera for solving the scale ambiguity problem. Our method is based on a concept called visual gyroscope and visual odometer discussed in more detail in [14].

The visual gyroscope is based on using a principle called a Manhattan Grid [15]. It arises from the fact that most urban scenes consist of straight lines in three orthogonal directions. These lines appear to intersect in three points called vanishing points. The locations of the vanishing points are defined by the orientation of the camera with respect to the scene and therefore the change in their location in consecutive images defines the change in the camera orientation. The principle of the visual odometer is based on looking at the motion of the image points of a static object. When the tracked objects are found from the ground plane, a principle called homography may be used for solving for the translation [16]. In our method, we use the prior information about the camera height and orientation from the visual gyroscope to solve for the scale ambiguity.

Previously, the method has been shown to provide good performance [1], but it is very dependent on the characteristics of the environment. Therefore, we are in the process of replacing the monocular camera with a RealSense D435 camera providing depth information for each pixel via structured light and dual IR cameras. This will liberate us from the complicated process of solving for the scale ambiguity and therefore from the restrictive requirement of extracting the orthogonal lines in the scene. However, the camera characteristics greatly affect the performance of the VO [17]. Therefore, in our first experiment we will compute the original visual gyroscope and odometer solution using the RealSense color images. In the future research, we will use the depth information for computing a conventional visual gyroscope solution and will use sophisticated machine learning algorithms for improving the tracking performance.

Pedestrian Dead Reckoning

Foot mounted PDR utilizes an Inertial Measurement Unit attached to the shoe of the user [18]. This approach limits the error growth of inertial system that propagates the position and attitude of the sensor based on acceleration and turn rate measurements. During each step, when the foot is detected to be at standstill, the system makes a zero-velocity update (ZUPT) that is used as a pseudo measurement of velocity allowing limitation of velocity error growth.

Effective and accurate detection of stationary periods between steps is crucial for the foot mounted inertial navigation system. In this study we use the sum of squared of angular rates averaged over detection window as a detection value. This value is compared against a set threshold and a stationary period is assumed when this value is below the threshold. Method is simple but effective for straightforward walking motion as shown in multiple previous studies [19], [20], [21], [22], [23].

Because an IMU is self-contained the foot mounted navigation result is available at all times. However, the method has several drawbacks. One drawback is that ZUPT does not stop the accumulation of heading error and a complementary sensor is needed for this. Another drawback is that any sensor mounted on the shoe of the user needs to be compact and lightweight. Small low-cost sensors tend to have high measurement noise which is made worse by high dynamics of the foot. Because of these drawbacks, intelligent fusion methods of inertial navigation and other sensors should compensate the limitations of the foot mounted sensors.

One way to mitigate the effect of the noise caused by the high foot movement dynamics is to recognize the user's motion context and adapt the navigation algorithm based on that information. IMUs are commonly used also in movement recognition [24], so there is no need to add other sensors to those used for navigation. The sensor readings are used in a suitable machine learning algorithm in order to detect whether the user is running, walking or crawling, for instance. The motion context can be used for example to set different ZUPT threshold for walking and running [24][25], which has been shown to improve navigation performance [24][25][26].

Combined System Design

The intent of the CANDO project is to produce a well integrated shoulder mounted sensor package which will comprise each of a multi-frequency RTK GNSS module for outdoor initialization, a tactical grade MEMS INS, radio links for both ranging via UWB and Chirp Spread Spectrum (CSS), communication with foot-pod sensors as well as a camera module with both traditional color and structured light based stereo Infrared (IR) 3D imagers with sufficient compute power for real-time processing of data. A block diagram of the combined system is shown in Figure 1.

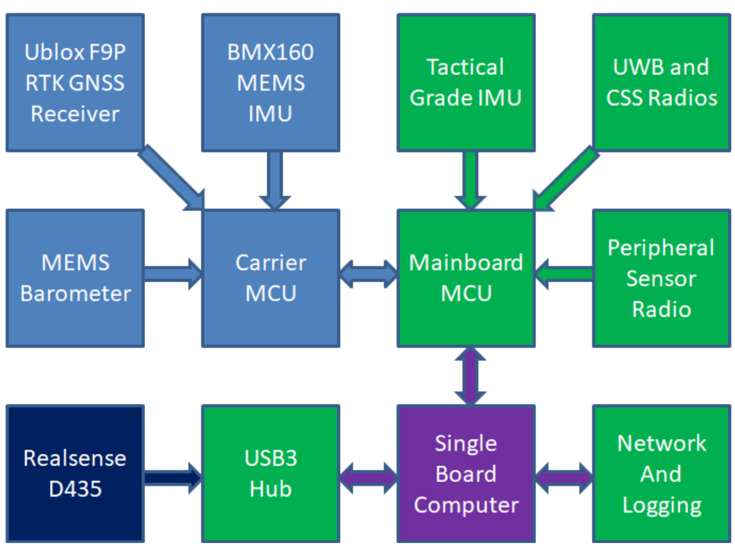

Figure 1: Block diagram of CANDO project combined navigation system.

The testing date set for evaluating the performance of this system is November 2019, and as such at the time of the drafting of this paper, initial results had to be collected via a mock-up consisting of previous generation Collaborative Navigation Version 3 (CNV3) [11] shoulder unit hardware modules combined with separately logged and manually synchronized VO on the primary user only and PDR sensor pods on three of the four users entering the building.

Test Setup and Data Collection

In order to ensure consistency between repeated test runs, each of the participating users was issued a set of instructions detailing what actions they were to take at which point in the test sequence, as well as a stop watch to keep actions synchronized as tightly as possible. All users were issued with CNV3 shoulder units as described in [11], and users 1, 2 and 4 with Xsens Awinda wireless IMUs for foot mounted PDR. User 1 was also equipped with an intel RealSense D435 3D camera mounted semi-rigidly to the same Modular Lightweight Load-carrying Equipment (MOLLE) vest fixture as the shoulder unit to try to maintain consistent alignment (Figure 1), as well as a backpack borne Novatel SPAN system based on an ISA-100C INS to establish the reference trajectory (Figure 2).

The specific testing steps are listed in Table 1:

Table 1: Test procedure.

Step #	Start time	Action	Note
1	N/A	Stand in a line at starting point facing approximately due East.	SPAN reference ready
2	N/A	Commence logging of Awinda foot sensors. Activate CNV3 shoulder units.	
3	0:00	Synchronize and start stopwatches. Stand still for static initialization.	
4	1:30	All users start outdoor calibration route.	
5	7:00	Users 1,2,3,4 enter the building, GNSS denial begins.	GNSS denial onset
6	7:00+	Users 1,2,3,4 proceed through lobby, right to main building and up two flights of stairs to 2nd floor.	
7	8:00	At the 8 minute mark, user 4 waits in the 2nd floor hall, while users 1,2, and 3 move together towards the West end of the building.	
8	8:30	At 8:30, user 3 waits at the west end of the building while users 1 and 2 proceed together to the stairwell, up two additional flights of stairs to the 3rd floor, and through the security door to the lab area.	
9	9:30	At 9:30 user 2 waits in the lab while user 1 proceeds up an additional flight of stairs to the attic, and out on to the roof area.	
10	10:30	At 10:30 user 1 returns inside and downstairs to the lab area.	
11	11:00	At 11:00 user 1 and 2 follow the same route back to the west end of the 2nd floor where user 3 is waiting.	
12	12:00	At 12:00 users 1, 2 and 3 follow the same route back to the 2nd floor hall where user 4 is waiting.	
13	12:30	At 12:30, users 1, 2, 3 and 4 return to the lobby, exit the building, and return to the test start point.	GNSS signal returns 13:00
14	15:00	At approximately 15:00 all users turn off the CNV3 units.	

Figure 2: USER 1 with shoulder unit and RealSense depth camera preparing for mock-up system testing. The testing venue building is visible in the background.

Figure 3: Rigid frame backpack holding ISA-100C based SPAN reference system.

Since the intended final design of the combined system to be tested at the end of the CANDO project in November 2019 will include a Ublox F9P multi-frequency receiver module, the design for the GNSS module based on this receiver was started in February 2019 and fabricated long before the tests were carried out, but repeated delays in the shipment of the stacked patch antenna round which the GNSS module printed circuit board was designed made this infeasible. To work around this missing RTK data source the GNSS module from the CNV3 shoulder units was utilized for all users, while an 'entry level RTK' solution for user 1 was simulated by artificially degrading the output of the reference trajectory with dm level white noise.

Test Results

In order to establish error profiles for the users operating indoors a Novatel SPAN system was used to estimate a reference trajectory through the office environment. To optimize the reliability of this reference trajectory, post processing was utilized via the Inertial Explorer software with forward-backward multi-pass processing, and the recently released pedestrian motion profile selected. The combination of these processing options with the approximately 30 second long window at the midpoint of the test during which User 1 bears the reference system proceeds to the roof and has open sky visibility allows the production of a reference trajectory with a peak reported standard deviation of less than 0.29 m in each axis at peak, and an average of approximately 0.10 m in each axis on average during the nearly six minutes of indoor operation, as reported by the Inertial Explorer software.

To determine the error profile of User 1, reference trajectory is sampled at 1 Hz during the indoor operations phase of the test, and the closest temporal match from the CNV3 system outputs is compared to form an error magnitude at each 1 Hz reference epoch. For User one the reference trajectory is shifted in the body frame to eliminate the static offset between the reference system and the shoulder unit producing error estimates as low as several centimeters during open sky conditions, suggesting that it is safe to consider the error estimates accurate to the dm level.

To determine the error profiles of Users 2, 3 and 4, the facts that the actions of the users are synchronized via stop watches, and that each of the users are left at static positions at known times are exploited to generate virtual reference trajectories for each of these users by modifying the main reference trajectory to stay at a fixed position through the period where the respective user was static. For example per Table 1, User 2 remains static between test period 9:30 and 11:00 in the 3rd floor lab while User 1 with the physical reference system proceeds up to the roof. By generating a modified reference trajectory that appears remain static in the lab during this interval, a continuous error trajectory for User 2 can be formed though with the obvious limitation of multiple meters of uncertainty in the error statistics produced due to the physical separation between the users. This process was repeated to produce virtual reference trajectories for users three and four.

In order to demonstrate the contributions of various system components to the final accuracy, the data was processed first with each user utilizing only the self-contained sensors within the CNV3 shoulder units (no foot pods, no visual odometry for User 1, and no user to user ranging links), second with the PDR and VO contributions added, and finally with the UWB user to user ranging links in the shoulder units activated. Plots of estimated error over time are shown in Figure 4, Figure 5 and Figure 6, while maximum and RMS errors of these respective test outcomes are presented in Table 2, Table 3, and Table 4.

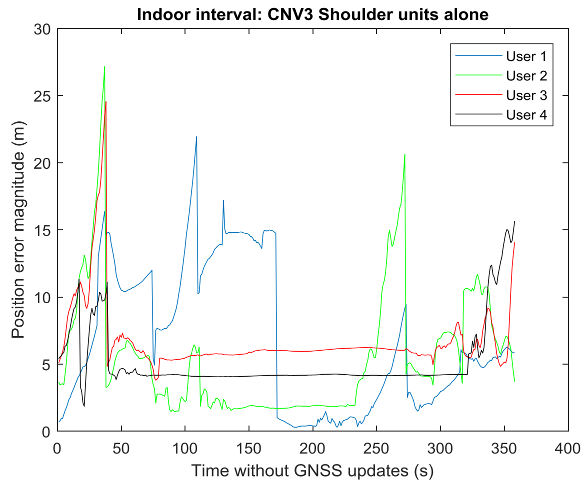

Figure 4: Position error for each user when using only shoulder unit sensors during approximately six minute indoor navigation.

Table 2: Performance of shoulder units alone.

	Error Max. (m)	Error RMS. (m)
User 1	21.9	8.7
User 2	27.2	7.3
User 3	24.5	7.2
User 4	15.6	5.8

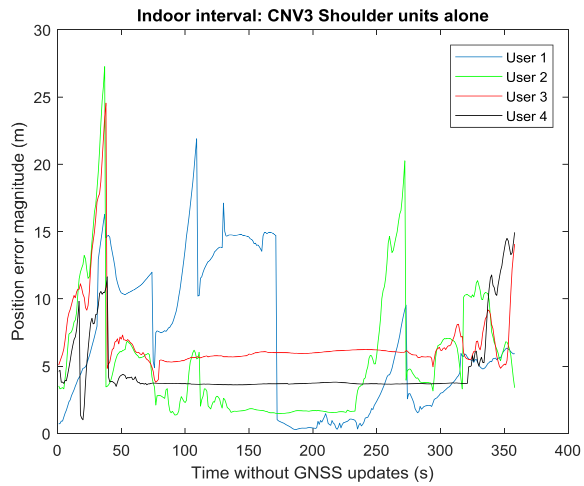

Figure 5: Position error for each user when using shoulder unit sensors, PDR foot pods for users 1, 2 and 4, as well as VO for User 1.

Table 3: Performance of shoulder units alone.

	Error Max. (m)	Error RMS. (m)
User 1	21.9	8.6
User 2	27.3	7.1
User 3	24.5	7.2
User 4	15.3	5.3

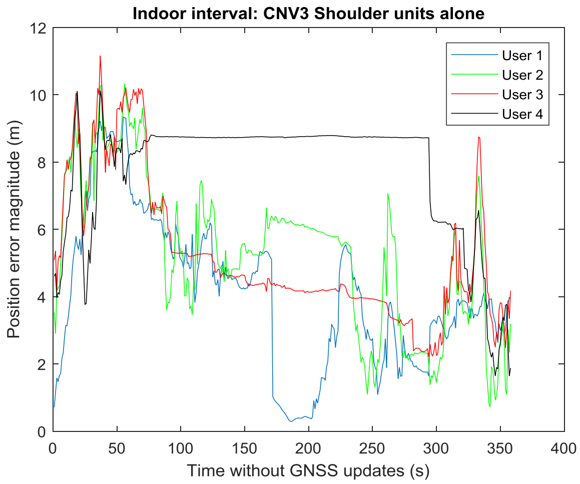

Figure 6: Position error for each user when using shoulder unit sensors including UWB collaborative navigation links, PDR foot pod sensors for Users 1, 2 and 4, as well as VO for user 1.

Table 4: Performance of shoulder units alone.

	Error Max. (m)	Error RMS. (m)
User 1	9.3	4.7
User 2	10.3	5.7
User 3	11.2	5.6
User 4	10.1	8.0

Analysis and Discussion

The (in)accuracy of the baseline shoulder system is understandable in the context of a shoulder mounted mobile system with a tactical grade MEMS INS, but is hardly sufficient for relating the reported position of the users to their actual location inside the building at anything approaching 'room level' accuracy which the authors consider to require typical uncertainties of less than 5 m. The addition of foot mounted PDR pods helps, principally by limiting error buildup during extended periods without ZUPTs, though the contribution of the foot pods and VO to the solution is disappointingly small. In the case of the foot pods it is in part related to the simple algorithm used for fusing the PDR solution with the other data sources which presently only estimates the local level frame displacement over chained two second windows. When processed separately and independent of the PDR, it was found that the contribution of VO while positive was also not substantial and not a good use of resources in terms of bandwidth, disk space or processing power required to exploit it compared to the other navigation sensors used here which can be processed in real-time on the microcontroller built in to the CNV3 shoulder units as opposed to requiring a multi-core laptop or desktop to post process. Exploitation of the UWB collaborative navigation radio links between users improves the navigation solution by reducing peak errors, reducing RMS errors (generally though not in the case of User 4), and also driving correlation between the error states of the users which beneficially makes it much clearer when users are operating in close proximity to one another.

Based on the results of the tests presented in this paper, the development of the new generation of shoulder units which will include RTK GNSS as well as wireless links to optional foot pod sensors for each user and a camera will proceed, though the emphasis will shift from use of VO to exploration of SLAM based methods of visual data processing. Currently the 3D imaging and structured light capabilities of the intel RealSense camera have not been required or used as the testing environments have all been fully illuminated, but it is within the desired range of features to operate in darkened or smoky environments, and it is desirable to improve the performance benefit of using camera data beyond what is offered by the implemented VO algorithms. Before the final system hardware is prepared a follow-on set of tests will be conducted with the depth sensing camera rigidly mounted to the SPAN reference system frame to provide insight to how the VO algorithms could be enhanced by providing estimates of attitude and position changes between frames as will be available in the final system.

Acknowledgements

The authors would like to thank the NATO Science for Peace and Security (SPS) Programme office for their support of project G5406, under which the tests documented in this paper were conducted.

REFERENCES:

1. Ruotsalainen L., Kirkko-Jaakkola, M., Rantanen, J. and Mäkelä, M. "Error modelling for multi-sensor measurements in infrastructure-free indoor navigation". Sensors 18(2), 2018, 590.
2. Mäkelä, M., Rantanen, J., Kirkko-Jaakkola, M. and Ruotsalainen, L. "Context Recognition in Infrastructure-Free Pedestrian Navigation—Toward Adaptive Filtering Algorithm". IEEE Sensors Journal 18(17), 2018, 7253-7264.
3. *Ortiz, M., De Sousa, M., and Renaudin, V. "A New PDR Navigation Device for Challenging Urban Environments". J. Sens. 2017*
4. R. Garello, L. Lo Presti, G. E. Corazza, and J. Samson, "Peer-to-Peer Cooperative Positioning Part I: GNSS-Aided Acquisition," InsideGNSS, vol. March/April, 2012.
5. N. Patwari, J. N. Ash, S. Kyperountas, A. O. Hero III, R. L. Moses, and N. S. Correal, "Locating the Nodes: Cooperative localization in wireless sensor networks," IEEE Signal Process. Mag., vol. 22, no. 4, pp. 54–69, Jul. 2005.
6. H. Wymeersch, J. Lien, and M. Z. Win, "Cooperative Localization in Wireless Networks," Proc. IEEE, vol. 97, no. 2, pp. 427–450, Feb. 2009.
7. J. Rantakokko et al., "Accurate and Reliable Soldier and First Responder Indoor Positioning: Multi-sensor Systems and Cooperative Localization," IEEE Wirel. Commun., vol. 18, no. 2, pp. 10–18, Apr. 2011.
8. N. A. Alsindi, B. Alavi, and K. Pahlavan, "Measurement and Modeling of Ultrawideband TOA-Based Ranging in Indoor Multipath Environments," IEEE Trans. Veh. Technol., vol. 58, no. 3, pp. 1046–1058, Mar. 2009.
9. S. Särkkä, "Bayesian Filtering and Smoothing". Cambridge University Press, 2013.
10. M. Mäkelä, M. Kirkko-Jaakkola, J. Rantanen, and L. Ruotsalainen, "Proof of Concept Tests on Cooperative Tactical Pedestrian Indoor Navigation," in 2018 21st International Conference on Information Fusion (FUSION), 2018, pp. 1369–1376.
11. A. Morrison, N. Sokolova, T.V. Haavardsholm, O.K. Hagen, T.O. Opsahl, K.B. Anonsen, and E.H. Eriksen, "Collaborative indoor navigation for emergency services personnel," 2017 IEEE Aerospace Conference, Bozeman, MO, March 2017.
12. Morrison A., Sokolova N. and E. Holthe Eriksen (2015), Collaborative Navigation for Defense Objectives, Proceedings of IEEE/2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 13-16 October 2015, Banff, Alberta, Canada.
13. A. Santos, L. Tarrataca, and J. Cardoso*, "An analysis of navigation algorithms for smartphones using J2ME,"* in MobileWireless Middleware, Operating Systems, and Applications, ser. LNICST. Springer Berlin Heidelberg, 2009, vol. 7, pp. 266–279.
14. Ruotsalainen, L. "Visual gyroscope and odometer for pedestrian indoor navigation with a smartphone". Proceedings of *25th International Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2012), Nashville, TN, September 2012.*
15. J. Coughlan and A. Yuille, "Manhattan World: Compass direction from a single image by Bayesian interference," in Proc. 7th IEEE International Conference on Computer Vision, Kerkyra, Greece, Sep. 20–27, 1999, pp. 1–10.
16. R. Hartley and A. Zisserman, Multiple View Geometry in Computer Vision, 2nd ed. Cambridge, UK: Cambridge University Press, 2003.
17. L. Ruotsalainen, J. Bancroft, G. Lachapelle, H. Kuusniemi, R. Chen. "Effect of camera characteristics on the accuracy of a visual gyroscope for indoor pedestrian navigation", 2012, Ubiquitous Positioning, Indoor Navigation, and Location Based Service (UPINLBS)
18. E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," IEEE Computer Graphics and Applications, vol. 25, no. 6, pp. 38–46, Nov. 2005.
19. I. Skog, P. Handel, J.-O. Nilsson, and J. Rantakokko, "Zero-velocity detection—An algorithm evaluation," IEEE Transactions on Biomedical Engineering, vol. 57, no. 11, pp. 2657–2666, Jul. 2010.
20. L. Ojeda and J. Borenstein, "Non-GPS navigation for security personnel and first responders," The Journal of Navigation, vol. 60, no. 3, pp. 391–407, 2007.
21. J. Rantakokko, P. Strömbäck, E. Emilsson, and J. Rydell, "Soldier positioning in GNSS-denied operations," in Proc. of the Sensors and Electronics Technology Panel Symposium (SET-168) on Navigation Sensors and Systems in GNSS Denied Environments, Izmir, Turkey, 2012.
22. L. Ruotsalainen, M. Kirkko-Jaakkola, J. Rantanen, and M. Mäkelä, "Error modelling for multi-sensor measurements in infrastructure-free indoor navigation," Sensors, vol. 18, no. 2, p. 590, 2018.
23. R. Zhang, F. Hoflinger, and L. Reindl, "Inertial sensor based indoor localization and monitoring system for emergency responders," IEEE Sensors Journal, vol. 13, no. 2, pp. 838–848, 2013.
24. M. Mäkelä, J. Rantanen, M. Kirkko-Jaakkola and L. Ruotsalainen, "Context Recognition in Infrastructure-Free Pedestrian Navigation—Toward Adaptive Filtering Algorithm," in IEEE Sensors Journal, vol. 18, no. 17, pp. 7253-7264, 1 Sept.1, 2018. DOI: 10.1109/JSEN.2018.2847038

25. Wagstaff, B., Peretroukhin, V., & Kelly, J. (2017, September). “Improving foot-mounted inertial navigation through real-time motion classification”. In 2017 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 1-8). IEEE.
26. Rantanen, J., Mäkelä, M., Ruotsalainen, L., & Kirkko-Jaakkola, M. (2018, September). ”Motion Context Adaptive Fusion of Inertial and Visual Pedestrian Navigation”. In 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN) (pp. 206-212). IEEE.