Mobile Indoor Navigation: From Research to Production

Yevhen Chervoniak, Ievgen Gorovyi
It-Jim
Kharkiv, Ukraine
eugenecher94@gmail.com, ceo@it-jim.com

***Abstract*—indoor positioning systems in GPS-denied environments are rapidly becoming popular. Various options are commonly available (BLE, Wi-Fi, ultra-wideband, ultrasonic, etc.). The key challenge is to provide accurate, and stable real-time user location at a low cost.**

In this paper, we present the research and production details of the developed hybrid indoor localization and navigation system (HILN). The proposed technical solutions are based on cheap Bluetooth beacons and mobile sensors. In particular, we describe two separate positioning pipelines for open spaces and narrow environments. The scheme of efficient fusion of inertial navigation system (INS) and BLE navigation system is proposed. All the developed solutions are integrated into the mobile indoor software development kit (SDK). Its main components are briefly mentioned. Our mobile positioning system provides 1-2m accuracy and works on Android and iOS devices in a real-time basis.

Keywords—indoor positioning, mobile indoor SDK, Bluetooth beacons, BLE, IMU, sensor.

I. Introduction

Millions of people use positioning and navigation services daily. It is known, that the global positioning system (GPS) provides acceptable accuracy almost at any point on the globe. The problem is that such a system fails in indoor environments and places where the connection between a user and satellites is lost [1]. For instance, at the shopping malls, airports, museums, stadiums, hospitals, etc. This challenge indicates the importance of separate alternatives like indoor positioning and navigation systems (IPNS) [2].

There are many options for the design of a mobile IPNS. A popular technique is based on the usage of cheap Bluetooth low energy (BLE) beacons or Wi-Fi hotspots together with mobile sensors (accelerometer, gyroscope, and magnetometer) [3-6]. Many companies like Estimote [7], Infsoft [8], Navigine [9] provide their software development kits (SDK) for integration into mobile IPNS. Indeed, smartphones are available for everyone and this means that IPNS can be constructed with no cost for the end user. In the paper, we consider the mobile IPNS system based on BLE and in-built smartphone inertial measurement units (IMU).

The development of a stable indoor positioning engine and its integration into a mobile device is a challenging task [2, 4, 10, 16]. Bluetooth signal may lose the data packets; beacon signal strength significantly fluctuates causing high uncertainties of the location estimate. As for mobile IMU, its data are noisy and demonstrate drift causing substantial errors in the user positioning. In this work, we describe how we have overcome the problems and limitations. It is important that both technical and production details are discussed.

Firstly, we describe how we have built the hybrid positioning pipeline (Section II). In particular, the developed solutions for stable location estimation in both open spaces and narrow environments are considered. Moreover, BLE+IMU fusion scheme is proposed. It is shown, that usage of particle filter [11] for the combination of beacons and mobile sensors data provides a high accuracy (around 1-2m) and stability in production. Section III contains useful information about our mobile indoor SDK and its structure.

II. Developed Positioning Pipeline

A. BLE Positioning in Open Space

BLE beacons are quite popular nowadays mainly due to low price and independence from an external power source [2, 4, 10]. There are few most widely used data transmission standards like iBeacon (Apple) [12], Eddystone (Google) [13] and AltBeacon (Radius Networks) [14]. The idea is straightforward: to provide the basic information about a beacon including its unique identifier (ID), its location and radio signal strength indicator (RSSI) measured in dBm [3, 10, 15, 16].

Knowing the power of the transmitted and received RSSI, it is theoretically possible to estimate the distance based on the so-called path-loss propagation model [10, 15, 16]. A basic scenario is trilateration [17] when we know distances from triplet (three beacons) and retrieve the user's location instantly. Unfortunately, in practice, it does not work well because of significant RSSI fluctuations [16] (due to transmitter and receiver noise, multiple reflections, indoor signal interference). Another challenging problem is BLE packets loss, which leads to incorrect positioning.

We have built a custom BLE positioning pipeline (fig. 1) based on numerous experiments. Firstly, the Kalman RSSI filter is applied [10, 18]. It solves two problems at once: prediction of RSSI for a given beacon if its packet is lost for some reason. Secondly, the filter performs smoothing of RSSI fluctuations. The triplet filter is an important part of the algorithm as well, since it allows to control the beacon IDs

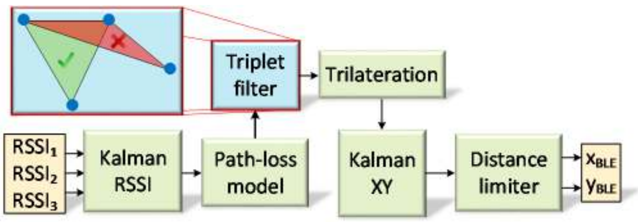

Fig. 1. BLE positioning steps

used in trilateration avoiding incorrect triplet choice. As a result, the unnecessary user position fluctuations can be significantly reduced. Kalman XY is the so-called extended Kalman filter [19]. It provides additional stabilization of the user location estimate [10]. Finally, the distance limiter helps to avoid unexpected fast jumps of the location estimate. Indeed, a walking user is not able to pass long distance just in few seconds.

The problem is that even sophisticated signal processing techniques could not provide high positioning precision. This is the main reason to use mobile IMU to overcome this challenge.

B. BLE Positioning in Narrow Environments

It is important to mention, that signal propagation and, hence, applied signal processing algorithms, may differ depending on building geometry. For instance, in narrow environments, the trilateration-based BLE positioning is not an optimal option since it requires too many beacons, while not providing acceptable accuracy due to significant signals interference. For this purpose, we have built an alternative approach called proximity positioning. In contrast to common trilateration, this method works well in narrow environments (corridors) with a small number of beacons.

Let's consider the main steps of the developed methodology (Fig. 2). On the first stage, the so-called connected graph is created. The beacons are nodes, the lines connecting them are edges (fig. 2a). The two nearest beacons (reliable beacons) are defined according to their RSSI. The edge connecting them is called the main edge. Then the candidate positions are defined. If to represent the distance to a beacon as a circle, then all candidates are intersections of all circles and the main edge (fig. 2a).

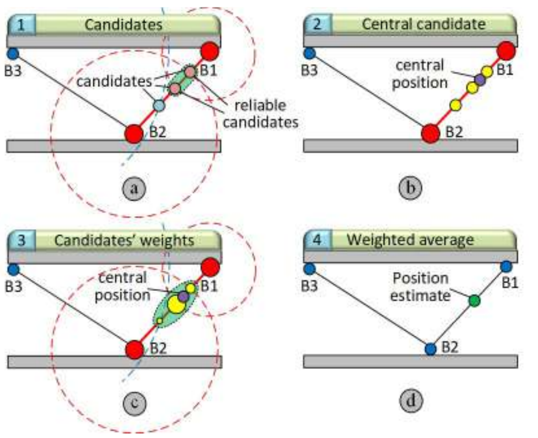

Fig. 2. Principle of proximity positioning: definition of candidates (a), calculation of the central position (b), candidates weighing (c), and the resulting position estimation (d)

The candidates which belong to the reliable beacons are called reliable candidates. On the second stage, the central position is calculated as an average of the reliable or all available candidates (fig. 2b). On the third stage, each candidate is weighted according to the distance from the central position to the beacon-owner of the candidate (fig. 2c). Finally, the resulting position is a weighted average of all candidates (fig. 2d). The tests have shown that the proximity algorithm provides stable positioning with the small number of beacons used.

C. Hybrid Indoor Localization and Navigation

It is known, BLE positioning accuracy is moderate and often not enough for some real cases. In order to enhance positioning accuracy, the INS is commonly used as a supplementary technique. The user location in INS is estimated by the processing of IMU (accelerometer, gyroscope, and magnetometer) signals. Mobile sensors provide quite a high instant accuracy but the main problem is they demonstrate a significant drift (magnetometer does not) over a long time period [20, 21]. It was found [10], that such drift is crucial even for user movement during a few seconds. From another side, the BLE positioning is drift-free. This gives an idea for fusion of data from two signal sources. The hybrid indoor localization and navigation (HILN) system is developed for this purpose. However, the IMU data should be processed before the fusion. Let's consider this procedure.

The displacement in INS is estimated by double integration of the acceleration. In order to reduce drift, the accelerometer data should be integrated only when the user is moving. Thus, there is a need for the step detector [4, 5, 10, 22]. In the basic version of step detector, the acceleration module is compared with a constant threshold. If it is exceeded, then it is supposed, that the user has made a step. However, such a detector is dependent on the user gait (walking, running, moving upstairs etc.). Moreover, the step length is not estimated since the step boundaries are unknown.

Fortunately, this is not a problem for step detectors based on step pattern recognition [22]. Such detectors distinguish each stage of the step. The user's gait is not a problem since the database of patterns of all gait types is a part of such step detectors. The problem is the step pattern recognition is applicable only in case of a foot-mounted or body-mounted accelerometer when the acceleration is measured accurately enough. This technique is not applicable in case of hand-held sensors (like a smartphone).

In our IPNS, the adaptive step detector is used. Step threshold is automatically adjusted according to the user gait dynamics. In addition, the step boundaries are detected by the algorithm [10]. The *s*-th step is supposed to start, if the module of global acceleration $a(i)_{global}$ increases while exceeding average acceleration $a(i)_{avg}$ at *i*-th time moment. The step is supposed to finish if the condition above is fulfilled and the step amplitude $a(s)_{\max} - a(s)_{\min}$ exceeds the threshold $thr(s-1)$ multiplied by a tuning factor *scale*. In addition, the key parameters are updated as follows:

$$a(i)_{avg} = w_{avg} \times a(i)_{global} + (1 - w_{avg}) \times a(i-1)_{avg} \tag{1}$$

$$\begin{aligned} thr(s) = w_{thr} \times \left[a(s)_{\max} - a(s)_{\min} \right] + \\ + (1 - w_{thr}) \times thr(s-1) \end{aligned} \tag{2}$$

where w_{avg} is the weight factor of the global acceleration, w_{thr} is the weight factor characterizing the impact of the *s*-th step amplitude on the threshold *thr(s)*.

Before the step detector runs, the acceleration is converted from local coordinate system (CS), defined by smartphone axes, to global CS, which axes are directed towards the Earth's center of mass and towards the magnetic north. For this purpose, the device orientation angles are estimated by AHRS (attitude and heading reference systems) algorithm. Then the acceleration coordinate system is rotated using rotation matrices or quaternion algebra [5, 10].

After the step boundaries are known, it is not a problem to estimate step length by double integration of acceleration. In order to reduce the cumulative error more efficiently, the so-called ZUPT (zero-velocity update) algorithm [23] is used. If the step is not detected, the velocity is reset (equalized to zero). After the step length is estimated, the distance limiter reduces it to a permissible value, if necessary. Now, the IMU data are ready for fusion with BLE data.

The particle filter (PF) [11] is a powerful tool for fusion of inertial and non-inertial positioning systems [4, 5, 10]. It consists of three iterative stages which are used after initialization. The seeding stage is done once (fig. 3a). This is a process of creation of the first generation of particles. They are randomly distributed over the whole map (if the user's initial location is unknown) or within some circular region around the user's initial position. The particles are moving according to the results of the INS part of HILN (fig. 3b). The positions of all particles are updated based on the user's step length. Then they get weights according to the distance to the user's BLE position (fig. 3c): the less distance, the greater the weight. If the particle is in the "forbidden" zone (a region where the user cannot walk) or if it has crossed this zone after relocation, its weight is equalized to zero and the particle is deleted. Finally, the number of particles must be brought back the initial amount, while the higher probability of getting to a new generation belongs to particles with higher weights (fig. 3d). The resulting position estimate is an average of the resampled particles.

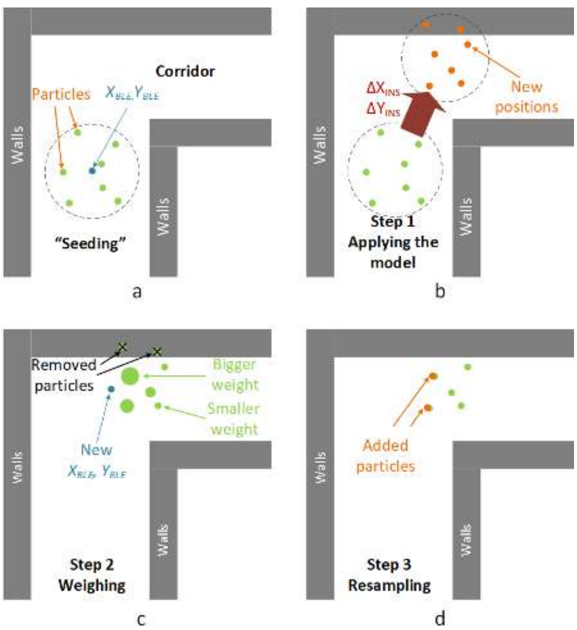

Fig. 3. Particle filter stages: seeding (a), applying the model (b), weighing (c), and resampling (d)

Fig. 4 summarizes the key steps of the developed HILN system. The INS part provides real-time device heading estimation as well as user steps information. The BLE part is used to eliminate the IMU drift and for proper control of the positioning dynamics. Finally, the particle filter does a good job on the fusion of signals from two sources (BLE+IMU). In all experiments held with hybrid HILN, the positioning accuracy was within 1-2m, which is comparable to existing commercial systems.

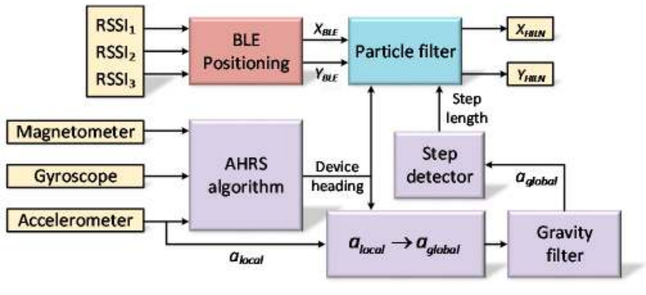

Fig. 4. HILN steps

III. Indoor Navigation in Production

It is important, that all developed positioning and navigation algorithms are integrated into the core of the mobile indoor navigation SDK. The developed system consists of several components: server, User application, Indoor tool, and additional utilities.

The server is intended for full control and management of indoor navigation back-end (Fig. 5). The system owner is setting up the building data and SDK configuration. A map and a mask are initially prepared. The mask indicates the allowed regions for the user location. The configuration file contains information about beacon positions and parameters. In addition, the navigation engine parameters can be controlled (for advanced users). In addition, the points of interest (POI) functionality is included. The system can indicate all users when they pass a particular map zone or a precise location. The navigation graph is used by SDK for user navigation and estimation of the distance to the chosen destination.

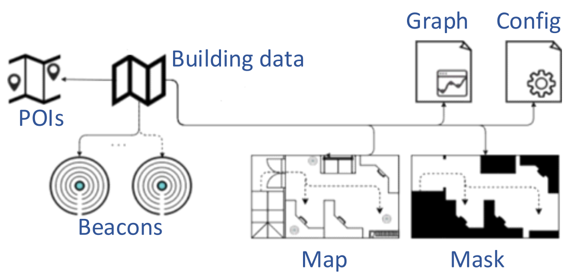

Fig. 5. Indoor server: high-level diagram

The fig. 6 illustrates an example of User application. The user can see his position in real-time, the application shows notifications near the configured POIs. Navigation feature is included as well. Thus, the user is able to choose the destination point, control the time and distance to the target.

The server and user applications are synchronized, which means that all users automatically obtain the notifications in case of changes of system configuration by an administrator. The mobile navigation SDK does not require GPS and permanent Internet connection and works in a real-time basis. The configuration of beacons, maps, and auxiliary data is done only once by an engineer. All parameters are automatically stored in the mobile Indoor tool (application for system configuration) and sent to the Indoor server.

Fig. 6. Indoor user application

We have tested our indoor SDK in several locations. It provides stable 1-2m positioning accuracy. In near future, we are planning to incorporate visual navigation engine based on simultaneous location and mapping (SLAM).

IV. CONCLUSIONS

We have presented the mobile indoor navigation SDK. From one side, the developed technical solutions were discussed. In particular, the multi-step BLE positioning pipeline including triplets filtering, Kalman filters for recovering of lost beacon packets and improvement of positioning stability. A custom step detector was created. An advantage of this solution is that it is able to adapt to the gait of a particular user. Finally, a novel IMU and BLE fusion scheme was developed, tested and integrated into a mobile SDK.

Some production details of the mobile indoor navigation SDK were described. In particular, User application, Indoor tool, the server, and additional configuration instruments.

It is demonstrated, that the developed technical solutions are robust enough for production level and usage on mobile devices without the need for Internet connection and GPS. The achieved accuracy of 1-2m in real-time makes the proposed system to be a good competitor to existing commercial products for indoor positioning and navigation purposes.

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REFERENCES

[1] H.A. Karimi, Indoor Wayfinding and Navigation, CRC Press, 2015.

[2] H.A. Karimi, Universal Navigation on Smartphones, Springer Science+Business Media, 2011.

[3] Streich, Katja . (2017, Julie 13). Technologies for Server-Based Indoor Positioning Compared: Wi-Fi vs. BLE vs. UWB vs. RFID [Web site]. Available: https://www.infsoft.com/blog-en/articleid/188/technologies-for-server-based-indoor-positioning-compared

[4] Tian, Qinglin et al. "A Hybrid Indoor Localization and Navigation System with Map Matching for Pedestrians Using Smartphones." Ed. Kourosh Khoshelham and Sisi Zlatanova. Sensors (Basel, Switzerland) 15.12 (2015): 30759–30783. PMC. Web. 14 Mar. 2018.

[5] Tian Q., Salcic Z., Wang K.I.-K., Pan Y. A Multi-Mode Dead Reckoning System for Pedestrian Tracking Using Smartphones. IEEE Sens. J. 2016;16:2079–2093. doi: 10.1109/JSEN.2015.2510364.

[6] S. Goswami, "Indoor Location Technologies", Springer Science+Business Media, 2013.

[7] https://estimote.com.

[8] https://www.infsoft.com.

[9] https://navigine.com.

[10] Ievgen Gorovyi, Feliks Sirenko, Alexey Roienko, Yevhen Chervoniak, "Positioning Algorithms for Indoor Navigation Using Sensors Fusion", Proc. of the International Conference on Indoor Positioning and Indoor Navigation (IPIN 2018), Sep. 24-27, 2018, Nantes, France, pp. 1-4.

[11] Del Moral, Pierre (1996). "Non Linear Filtering: Interacting Particle Solution". Markov Processes and Related Fields. 2 (4) pp. 555–580.

[12] A. Cavallini, "iBeacons Bible", 2015, [PDF], p.5, https://meetingofideas.files.wordpress.com/2015/09/beacon-bible-3-0.pdf.

[13] Radius Networks, 2014, https://github.com/AltBeacon/spec

[14] R. Amadeo, "Meet Google's "Eddystone" - a flexible, open source iBeacon fighter", Ars Technica, 2015, https://arstechnica.com/gadgets/2015/07/meet-googles-eddystone-a-flexible-open-source-ibeacon-fighter.

[15] Chuan-Chin Pu, Chuan-Hsian Pu and Hoon-Jae Lee (February 7th 2011). Indoor Location Tracking Using Received Signal Strength Indicator, Emerging Communications for Wireless Sensor Networks, Anna Foerster and Alexander Foerster, IntechOpen, DOI: 10.5772/10518. Available from: https://www.intechopen.com/books/emerging-communications-for-wireless-sensor-networks/indoor-location-tracking-using-received-signal-strength-indicator.

[16] Ievgen Gorovyi, Alexey Roenko, Alexander Pitertsev, Yevhen Chervonyak, Vitalii Vovk, "Framework for Real-Time User Positioning in GPS Denied Environments", Proceedings of the Signal Processing Symposium (SPSympo-2017), 12-14 Sept., 2017, Jachranka, Poland, pp. 1-5. doi: 10.1109/SPS.2017.8053695.

[17] A. Norrdine, "An Algebraic Solution to the Multilateration Problem", Proc. of the 3rd Internat. Condf. "Indoor Positioning and Indoor Navigation", Sydney, Australia, 2012.

[18] "What is the Kalman Filter and How can it be used for Data Fusion?" Robotics Math 16-811 Sandra Mau December 2005.

[19] Seoung-Hyeon Lee, "Method for Improving Indoor Positioning Accuracy Using Extended Kalman Filter," Hindawi, Daejeon 34129, Republic of Korea, 2016.

[20] Zhi, R. "A Drift Eliminated Attitude & Position Estimation Algorithm In 3D" Graduate College Dissertations and Theses, University of Vermont, 2016

[21] Abyarjoo F., Barreto A., Cofino J., Ortega F.R. (2015) Implementing a Sensor Fusion Algorithm for 3D Orientation Detection with Inertial/Magnetic Sensors. In: Sobh T., Elleithy K. (eds) Innovations and Advances in Computing, Informatics, Systems Sciences, Networking and Engineering. Lecture Notes in Electrical Engineering, vol 313. Springer, Cham.

[22] Ho, N.-H., Truong, P. H., & Jeong, G.-M. (2016). "Step-Detection and Adaptive Step-Length Estimation for Pedestrian Dead-Reckoning at Various Walking Speeds Using a Smartphone. Sensors" (Basel, Switzerland), 16(9), 1423. http://doi.org/10.3390/s16091423.

[23] Kyeong Park, Sang & Soo Suh, Young. (2010). A Zero Velocity Detection Algorithm Using Inertial Sensors for Pedestrian Navigation Systems. Sensors (Basel, Switzerland). 10. 9163-78. 10.3390/s101009163.