Improved PDR Localization via UWB-anchor based on-line calibration

Laura Giarré
Dept. of Engineering Enzo Ferrari (DIEF)
University of Modena and Reggio Emilia
Modena, Italy
laura.giarre@unimore.it

Federica Pascucci
Dept. of Engineering (DING)
University of Roma TRE
Roma, Italy
federica.pascucci@uniroma3.it

Simone Morosi and Alessio Martinelli
Dept. of Information Engineering (DINFO)
University of Florence - CNIT
Firenze, Italy
simone.morosi@unifi.it
alessio.martinelli@unifi.it

***Abstract*—In the present paper, we perform an on-line recalibration of a localization system which is based on the pedestrian dead reckoning technique by means of an anchor based Ultra Wide Band positioning. As a matter of fact a hybrid localization perspective is adopted that foresees the use of different (wearable) sensors to improve the localization accuracy; furthermore, it exploits the data to simultaneously build maps in unknown and uncertain environments. Comparisons of pedestrian dead reckoning localization with and without recalibration are shown by reporting the results of experiments that have been taken in a real environment.**

***Index Terms*—Localization, PDR, UWB, Sensor fusion**

I. Introduction

Indoor Localization is very important in many fields, such as localization of tourists, assistive technology, industry monitoring, robotics, e.g., navigation and planning, marketing and recommendations, and also in risk operations such as firefighters interventions [1], [2]. All these fields have a very high economical, technological and societal impact. As for assistive technologies, the possibility of helping low vision and blind person in navigating and localizing themselves inside unknown indoor building has a very high social impact. Many new methodologies have been attracted ICT scientists to tackle this problem [3]. There are 285M visually impaired people worldwide, among whom 39M are blind [4]. This number is increasing with aging of population which will be beneficial of new solutions for their autonomy. Moreover, rescue activities need for support especially when human perception fails, i.e. due to the presence of thick smoke and fire, which is the most common situation for rescuers.

Although GNSS is the leader technology in outdoor positioning, the pursue of an accurate position fix may become a complex issue in presence of harsh environments such as dense urban canyons, light shadowing, or more generally when GNSS signals cannot be received with a sufficiently high SNR [5].

In indoor environments, without GPS, the estimation of the position and attitude of a moving person is even a more complex task. The approaches for indoor localization investigated during the last decade can be roughly divided in three main areas:

- Infrastructure Based Localization: exteroceptive sensors are used, the users carry the sensor receiver and collect the information from the sensors deployed in the environment. A position fixing is calculated by using trilateration, triangulation, proximity, and fingerprinting [6].
- Dead-Reckoning: proprioceptive sensors are considered and the information provided by the human movements are used to compute the position of the user. PDR [6]–[10] involves three phases: step detection, step length estimation (SLE) and position update. Different techniques have been developed to identify step and compute the step length: most of the approaches consider Zero crossings/Zero velocity update [11], auto-correlation or template matching [12], spectral analysis [13].
- Hybrid System: proprioceptive and exteroceptive sensors provide information that are combined to obtain the position of the person.

This document is aimed at describing a novel technique for the fusion of two indoor localization algorithms, to improve both accuracy and efficiency. In particular, an Ultra Wide Band (UWB) anchor based localization technique is used both to calibrate and/or fuse the localization based on the Pedestrian Dead Reckoning (PDR) technique. Hereafter, we adopt a hybrid localization perspective that foresees the use of different (wearable) sensors to improve localization accuracy; furthermore, it exploits the data to simultaneously build maps in unknown and uncertain environments. The proposed approach envisages the use of wearable devices carried by the users and, when possible, low-cost anchors that are deployed in the considered environment. The wearable devices consist of a sensory system, i.e., an inertial platform integrating a tri-axial accelerometer, a tri-axial gyroscope, a tri-axial magnetometer, and an UWB blinker, while the anchors are four static UWB receivers that represent the components of the positioning and communication infrastructure and are connected to a processing unit . During the walking, the person is tracked by algorithms running on the processing unit. With respect to the foot mounted Inertial Measurement Unit (IMU) [14], the proposed waist mounted IMU reduces the possibility of damages. Moreover, it downgrades the PDR performance, since the zero-velocity update to determine the step event and reset the bias, cannot be used.

Furthermore, the anchors that are deployed in the envi-

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ronment will provide significant information to facilitate the operations of the persons inside the scenario. In contrast with literature, where localization is mainly based on BLEs (Bluetooth Low Energy devices) [15], [16], here the landmarks will be deployed to support IMU-based localization algorithms.

The present paper considers a sensor fusion approach which merge data from IMU and UWB systems. Two different algorithms are proposed. In the first one, only a simple recalibration of the estimate is performed. The second one, by exploiting both PDR and UWB data, allows to correct the heading thus improving the overall system performances. In particular positioning data, when available through the anchors, are used in the Kalman filter to improve the performance and reduce the tracking errors.

The rest of the paper is organized as follows. In Section II the PDR algorithm is presented, while in Section III the anchor-based localization exploiting UWB is introduced. In Section IV the proposed sensor fusion method is detailed and its performances are presented and discussed in Section V. Finally, the conclusions are drawn in Section VI.

II. IMU TRACKING

A. Activity Recognition

The *Activity Recognition* identifies the type of motion that is made by the user. Currently only two activities are recognized, i.e., *standing still* and *walking*, since the user navigates in a two-dimensional environment. To perform the recognition task, the acceleration covariances are used: the relative parameters decrease significantly when the user is standing still. Thus, the *standing still* activity can be easily detected when the following relation holds

$$P_j \leq \alpha_j, \quad \forall j \in \{x, y, z\}$$

where $P_j = \text{cov}(a_{k-b_k,j}, \cdots, a_{k,j})$ in the time interval $[b - k_b, k]$ and α_j is a threshold, set by experimental trials.

B. Heading Estimation

The Heading Estimation computes the heading of the user, with respect to the Navigation Frame, i.e., the world coordinate system fixed in inertial space. The heading is calculated exploiting the measurements retrieved from gyroscope, accelerometer, and magnetometer. The measurements from gyroscope and accelerometer represent the angular rate and the acceleration, respectively: they are provided in the Body Frame, i.e., body-fixed coordinate system rigidly attached to the user. The magnetometer provides the attitude of the user in the Navigation Frame. The well known approach based on quaternion and Bayesian filtering is adopted to provide heading estimate, as in [17]. Specifically, the initial attitude of the user in the Navigation Frame is supposed known. At each time instant, it is updated by integrating the measurements provided by the gyroscope. When data from accelerometer and/or magnetometer are available, a refinement of the attitude estimate is performed. The output of the Bayesian filter is the attitude (i.e., the rotation matrix $\mathbf{R}_b^n$), the heading and the corresponding uncertainty (i.e., the covariance of the heading).

C. Position Estimation

The *Position Estimation* is computing the position (x, y) of the user with respect to the Navigation Frame. This module exploits data from the accelerometer and the rotation matrix $\mathbf{R}_b^n$ provided by the Heading Estimation. The matrix $\mathbf{R}_b^n$ is used to project the accelerometer in the Navigation Frame: therefore, the acceleration along the z-axis of the Navigation Frame corresponds to the acceleration on the vertical axes of the user.

The initial position is supposed known while the position of the user during *walking* is recursively computed, by estimating the length of the stride on step event detection i

$$\begin{bmatrix} x_i \\ y_i \end{bmatrix} = \begin{bmatrix} x_{i-1} \\ y_{i-1} \end{bmatrix} + l_i \begin{bmatrix} \sin \bar{\phi}_i \\ \cos \bar{\phi}_i \end{bmatrix} \tag{1}$$

where l_i is the displacement of the user between two step events with respect to the Navigation Frame and $\bar{\phi}_i$ is the average heading in the same time interval.

The step detection is obtained by using the human body dynamic associated with the human gait cycle. These events are detected by analyzing the local minima and the local maxima of the vertical acceleration signal. To this end, both peak detection and zero crossing algorithms are applied to identify the sharp changes to the vertical acceleration associated with the heel strike. These features are also exploited to compute the cardinality c_i of the set of samples to be processed to cope with different walking speed. During *walking* activity, the displacement l_i is estimated as proposed in [18]:

$$l_i = \beta \sqrt[4]{a_{i,z}^M - a_{i,z}^m}$$

where $a_{i,z}^M$ and $a_{i,z}^m$ are the maximum and the minimum vertical accelerations in the time interval $(k - c_i, k]$ and β is a parameter depending on the user and estimated by a calibration procedure. It is worth noticing that in [18] the IMU is placed near the Center of Mass (CoM) of the user and β represents the average length of a step. Here, the parameter β depends also on the position of the hand with respect to the body of the user. Considering this parameter, the uncertainty of the position estimate can also computed. Finally, the user displacement is

$$l_i = \begin{bmatrix} 0 \, 0 \end{bmatrix}^T$$

when the output of the classification phase is the *standing still*. During *standing still* the measurements collected from gyroscope and accelerometer are used to update the bias, that slowly changes over time.

III. UWB ANCHOR BASED LOCALIZATION

As for the calibration system, an Ultra Wide-Band (UWB) anchor based approach will be used: therefore, a set of static UWB receivers, that are defined as anchors, will be deployed in a test field to validate the expected results. Particularly, this system consists of three components: a blinker, 4 anchors, and a mobile tablet/smartphone [19]. The blinker is a mobile device which transmit the UWB signals to the anchors, which are the static devices representing the infrastructure of the positioning system. The master anchor is the communication centre of the positioning infrastructure: it transmits UWB signals to the slave anchors and coordinates a WiFi network to share data between the tablet/smartphone and all anchors [19].

As it is known, in a generic position-fixing localization system, the position of an object can be determined by knowing the distance between the object itself and a sufficient number of reference points in the space of interest. The distance between each object and the reference point is commonly determined by the transmission of radio signals. In a remote positioning configuration, the navigation object which is named as the blinker, transmits a ranging signal to the reference points, each of which will be able to determine the distance from the object by calculating the flight time of the signal. Once the distance between the blinker and each anchor has been defined, and the position on the space of each reference point is known, a positioning algorithm will be able to determine the position of the navigation object: particularly, the fixed anchors determine the ranging results that are transmitted to a master node which is able to determine the position of the blinker. The Time Difference of Arrival(TDOA) method requires that the anchor be synchronized temporally, while a synchronization between the anchor and the blinker is not necessary [6]. In a 2D context, at least three anchors are needed to determine the position of the blinker. The difference in ranging between each pair of anchor and blinker generates a hyperbola along which the blinker lies. The intersection of at least two hyperboles allows to uniquely define the position of the blinker. In the case of our work, both the reference points (anchors) and the navigation object (blinker) will physically implement the 802.15.4 UWB-2011 communication standard. The UWB system is used for the calibration of the position, i.e., to suppress the localization error after the use of the dead reckoning procedure. As a matter of facts, the correction of the position coordinates can be very effective if the orientation of the blinker/navigator as derived from the use of the UWB system is taken into account: this approach has also been considered in the tests.

A. The 802.15.4 UWB-2011 standard

The 802.15.4 UWB standard was proposed for communications within sensor networks. In 2011, a specific amendment defines its enhancement by inserting time stamping functions on a physical level, both for the transmission and reception phases. This allowed the adoption of the 802.15.4 UWB-2011 in localization contexts. This standard defines the Physical and MAC levels of the ISO/OSI protocol stack.

IV. Sensor Fusion

The sensor fusion is applied in two different scenarios. In the first one, only a calibration of the position is considered since the measurement from UWB anchors are not always available. On the contrary, in the second scenario, they are supposed continuously available and a correction on the heading is performed.

In both scenarios, Kalman filtering approach is adopted to merge the information provided by the pedestrian dead reckoning and the UWB anchors.

In the calibration scenario, the state of the KF is represented by the position of the user, i.e., $\hat{\mathbf{p}}_i = [x_i, y_i]^T$ and the prediction equation are

$$\begin{array}{rcl} \hat{\mathbf{p}}_{i|i-1} & = & \hat{\mathbf{p}}_{i-1|i-1} + \mathbf{B}_i l_i \\ \mathbf{P}_{i-1|i-1} & = & \mathbf{P}_{i-1|i-1} + \mathbf{Q}_i \end{array} \tag{2}$$

where $\mathbf{B}_i = [\sin\bar{\phi}_i, \cos\bar{\phi}_i]^T$, $\mathbf{P}_{i-1|i-1}$ is the posterior covariance matrix and $\mathbf{Q}_i$ is the model uncertainty.

The correction step is performed by exploiting the position as it is computed by using the UWB anchors $\mathbf{p}_{i,U} = [x_{i,U}, y_{i,U}]^T$, when available; therefore

$$\begin{array}{rcl} \mathbf{S}_i & = & \mathbf{P}_{i|i-1} + \mathbf{R}_i \\ \mathbf{K}_i & = & \mathbf{P}_{i|i-1}\mathbf{S}_i^{-1} \\ \hat{\mathbf{p}}_{i|i} & = & \hat{\mathbf{p}}_{i|i-1} + \mathbf{K}_i(\hat{\mathbf{p}}_{i|i-1} - \mathbf{p}_{i,U}) \\ \mathbf{P}_{i|i} & = & (\mathbf{I}_{2\times 2} - \mathbf{K}_i)\mathbf{P}_{i|i-1} \end{array} \tag{3}$$

where $\mathbf{R}_i$ is the uncertainty related to the UWB measurements.

When the signal from the UWB anchors is continously available, also the heading can be corrected. The motion direction, indeed, can be computed from the position retrieved by the UWB system, as

$$\varphi_{i,U} = \operatorname{atan2}(\Delta y_{i,U}, \Delta x_{i,U})$$

where $\Delta x_{i,U} = x_{i,U} - x_{i-1,U}$ and $\Delta y_{i,U} = y_{i,U} - y_{i-1,U}$. In this scenario, the state of the system is represented by $\hat{\mathbf{x}}_i = [x_i, y_i, \vartheta_i]^T$ and prediction step of the model is performed as

$$\begin{array}{c} \hat{\mathbf{x}}_{i|i-1} = \begin{bmatrix} x_{i|i-1} \\ y_{i|i-1} \\ \vartheta_{i|i-1} \end{bmatrix} = \mathbf{A}\hat{\mathbf{x}}_{i-1|i-1} + \begin{bmatrix} l_i \cos\varphi_i \\ l_i \sin\varphi_i \\ \frac{\varphi_i}{2} \end{bmatrix} \\ \mathbf{P}_{i-1|i-1} = \mathbf{A}\mathbf{P}_{i-1|i-1}\mathbf{A}^T + \mathbf{Q}_i \end{array} \tag{4}$$

where

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \frac{1}{2} \end{bmatrix}$$

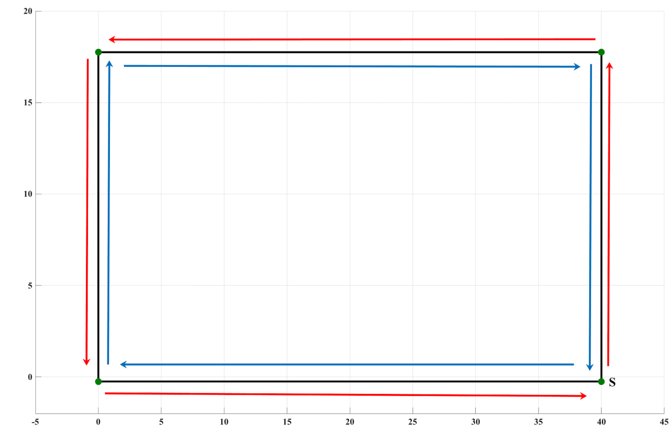
is the state transition matrix.

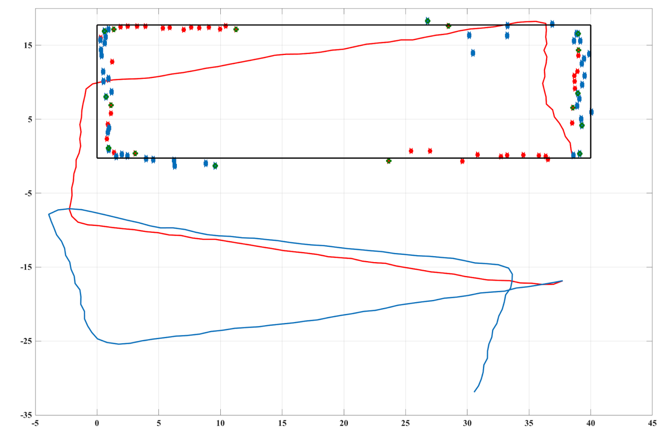
The correction step involves the heading and the equation are the following

$$\begin{array}{rcl} \mathbf{S}_i & = & \mathbf{P}_{i|i-1} + \mathbf{R}_i \\ \mathbf{K}_i & = & \mathbf{P}_{i|i-1}\mathbf{S}_i^{-1} \\ \hat{\mathbf{x}}_{i|i} & = & \hat{\mathbf{x}}_{i|i-1} + \mathbf{K}_i\left(\hat{\mathbf{x}}_{i|i-1} - \begin{bmatrix} x_{i,U} \\ y_{i,U} \\ \varphi_{i,U} \end{bmatrix}\right) \\ \mathbf{P}_{i|i} & = & (\mathbf{I}_{3\times 3} - \mathbf{K}_i)\mathbf{P}_{i|i-1} \end{array} \tag{5}$$

V. Experimental Validation

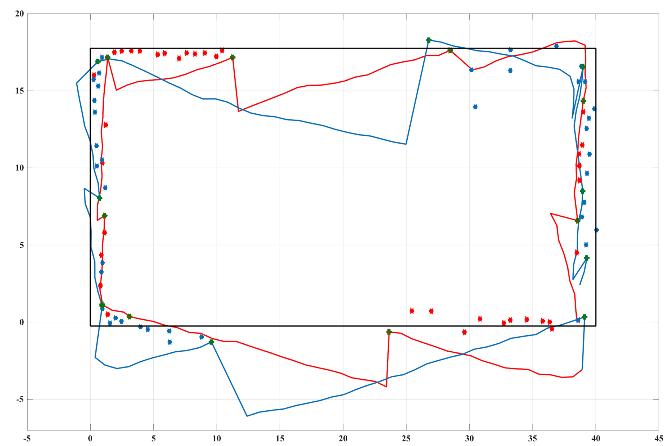
In order to validate the proposed methodologies, several experimental trials have been carried out. In this paper, for sake of space, only the results of one significant test are reported. As described in the following, the data collected by the UWB system and the IMU have been post-processed by using a MatLab tool developed by the Authors.

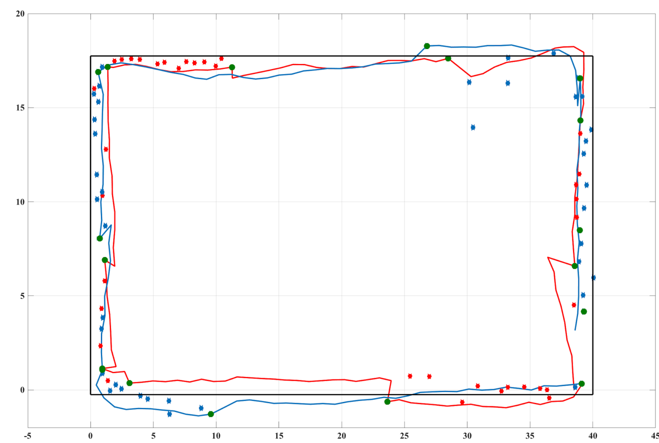




(a) Rectangular-path: green dots represent the position of the UWB nodes. S is the starting point.

(b) Rectangular-path: comparison among the PDR (red and blue solid lines) and UWB data. Green dots represent the calibration points.





(c) Rectangular-path: comparison among the position recalibrated PDR (red and blue solid lines) and UWB data. Green dots represent the calibration points.

(d) Rectangular-path:comparison among the pose recalibrated PDR (red and blue solid lines) and UWB data. Green dots represent the correction points.

Fig. 1. Rectangular-path test. The black rectangle represents the path, solid red and blu lines are the counterclockwise and clockwise paths respectively. Red and blue dots are the position retrieved with the UWB system during the counterclockwise and clockwise path respectively. The $(x$-$y)$ unit of measurement is $[m]$.

During the experiment shown in Fig. 1, a rectangular path is executed by the user two times. The user starts in the lower right position and walks along the perimeter of the rectangle counterclockwise; thereafter it turns to reach the starting point by traveling clockwise.

The setup used in the experiment is based on an ASUS ZenPhone 2 equipped with an internal Intel IMU, four static UWB receivers are placed at the corners of the test field that is illustrated in Fig.1, while a mobile blinker is equipped with the UWB transmitter; both the blinker and the anchors are supplied with a Decawave DWM1000 UWB transceiver [20] and a Li-Po battery-powered, whereas the anchors include also a WiFi module [21].The body location of the UWB transmitter, i.e., the blinker, is the upper back.

The mobile phone is attached to a belt to obtain a waist-mounted configuration: an Android app has been implemented to log and store the measurements of the IMU. The data sampling frequency is 80Hz. The DWM1000 chip is a UWB transceiver compliant with the IEEE 802.15.4-2011 standard that allows very accurate ranging measurements. These transceivers can transmit pulses that are few nanoseconds long with a bandwidth of 500 or 900 MHz and a frequency center that spans from 3.5 to 6.5 GHz. The high temporal resolution required to perform UWB communication allows an accuracy of the ranging measurements down to a few centimeters in LOS conditions. Due to its high bandwidth and spectrum usage, the transmit power density of the UWB transceivers is limited to -41.3 dBm/MHz to avoid inter-system interference. This restriction limits the operational range of the UWB transceivers, up to 300 m in LOS and 40 m in NLOS [20]. In this work, the DWM1000 UWB transceivers are configured to operate on channel 4 (900 MHz bandwidth with a center frequency of 3993.6 MHz), preamble length of 2048 symbols and a data rate of 850 kbps.

In Fig. 1(b) a comparison between the PDR and the position estimated by the UWB system is proposed. As can be noticed, the information gathered by the PDR is always available while the presence of UWB signal may be limited due to obstructions. However, the PDR estimation error grows over time due to the heading error and it is not possible to close the loop at the end of the counterclockwise round. On the contrary, the estimate of the UWB system is mostly reliable but for few outliers, that can be easily identified and introduce large errors.

In Fig. 1(c), the impact of the calibration algorithm is shown. According to the proposed approach, the position of the user is corrected when the UWB measurements are available. In this case, only a reduced number of UWB data has been considered to update the estimate. The position computed by the sensor fusion filter is able to track the user continuously. However, it is not reliable, as the heading error grows over time.

In Fig. 1(d), the result of the sensor fusion algorithm, when the heading measurement is available, is depicted. Even in this case, a reduced number of UWB measurements has been used. As can be noticed, the tracking error is considerably reduced. This approach, indeed, exploits both the accuracy of the UWB and the continuous availability of the data retrieved by the IMU.

VI. Conclusions

In this contribution, a localization system for human beings has been presented. The system is based on a sensor fusion approach, by merging data from the IMU and the UWB systems. Two different algorithms are proposed. In the first approach, only positioning measurements are considered, thus a simple recalibration of the estimate is performed. The second one, by exploiting both PDR and UWB data, allows to correct the heading, so improving the overall system performance.

Although the results are promising, there is still room for improvements. Future development will be devoted to extend the sensor fusion approach in order to develop a tight coupling between the IMU and the UWB sensors. Furthermore, data collected by the UWB will be used for estimating the PDR parameters (e.g., the parameter related to the length of the step, β, gyros and accelerometers bias, and the magnetometer distortion). Finally, different human activities will be recognized.

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References

[1] U.S. Fire Administration, Abandoned Cold Storage Warehouse Multi-Firefighter Fatality Fire Worcester, USFA-TR-134, 1999.

[2] L. Faramondi, F. Inderst, F. Pascucci, R. Setola, and U. Delprato, An Enhanced Indoor Positioning System for First Responders, International Conference on Indoor Positioning and Indoor Navigation, 2013.

[3] Pissaloux, E., et al. "Mobility of Visually Impaired People." Fundamentals and ICT Assistive Technologies, Springer Verlag, 2017

[4] World Health Organization, Vision impairment and blindness, http://www.who.int/mediacentre/factsheets/fs282/en/

[5] S. Morosi, A. Martinelli, E. Del Re, Peer-to-peer cooperation for GPS positioning, International Journal of Satellite Communications and Networking, Vol. 35, n. 4, July/August 2017, Pages 323-341.

[6] Groves, P. "Principles of GNSS, Inertial and Multisensor Integrated Navigation Systems." Artech House. 2nd Ed., 2013.

[7] Martinelli, A., et al."Probabilistic Context-aware Step Length Estimation for Pedestrian Dead Reckoning" IEEE Sensors 18.4 (2018): 1600-1611

[8] Basso, M. et al."Pedestrian dead reckoning based on frequency self-synchronization and body kinematics", IEEE Sensors Journal 17.2 (2017): 534-545.

[9] N. Fallah et al. Indoor Human Navigation Systems; A survey, Interacting with Computers, Oxford Journals. 25:1 pp. 21–33, February 2013.

[10] Kang, W. et al.. "SmartPDR: Smartphone-based pedestrian dead reckoning for indoor localization." IEEE Sensors15.5 (2015): 2906-2916

[11] P. Goyal, V. J. Ribeiro, H. Saran, and A. Kumar. "Strap-down pedestrian dead- reckoning system." in 2011 International Conference on Indoor Positioning and Indoor Navigation, pages 1-7, 2011.

[12] H. Ying, C. Silex, A. Schnitzer, S. Leonhardt, M. Schiek, S. Leonhardt, T. Falck, P. Mahonen, and R. Magjarevic. 4th international workshop on wearable and implantable body sensor networks, 2007.

[13] H. Liu, H. Darabi, P. Banerjee, and J. Liu. Survey of wireless indoor positioning techniques and systems. IEEE Trans. Syst. Man Cybern. C. Appl. Rev., 37(6):1067-1080.

[14] Ruiz, A., et al. "Accurate pedestrian indoor navigation by tightly coupling foot-mounted IMU and RFID measurements." IEEE Trans. on Instrumentation and measurement 61.1 (2012): 178-189

[15] Pavel et al, Improving Indoor Localization Using Bluetooth Low Energy Beacons, Mobile Information Systems, 2016.

[16] S. S. Chawathe, "Beacon Placement for Indoor Localization using Bluetooth," 2008 11th International IEEE Conference on Intelligent Transportation Systems, Beijing, 2008, pp. 980-985

[17] F. De Cillis, L. Faramondi, F. Inderst, S. Marsella, M. Marzoli, F. Pascucci, S. Setola, Hybrid Indoor Positioning System for First Responders, in IEEE Transactions on Systems, Man, and Cybernetics: Systems, 2017.

[18] H. Wienberg, Using the ADXL202 in Pedometer and Personal Navigation Applications, *Analog Devices AN-602 application note*, 2002.

[19] Paoli, M., et Al.: Individual Tracking Method and System. Italy Patent Pending, No 102017000062080 (UA2017A004096) (June 2017)

[20] Decawave Company. https://www.decawave.com/

[21] Espressif Systems Company. https://www.espressif.com