*Article*

# Many Ways Lead to the Goal—Possibilities of Autonomous and Infrastructure-Based Indoor Positioning

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**Abstract:** There are many ways to navigate in Global Navigation Satellite System-(GNSS) shaded areas. Reliable indoor pedestrian navigation has been a central aim of technology researchers in recent years; however, there still exist open challenges requiring re-examination and evaluation. In this paper, a novel dataset is used to evaluate common approaches for autonomous and infrastructure-based positioning methods. The autonomous variant is the most cost-effective realization; however, realizations using the real test data demonstrate that the use of only autonomous solutions cannot always provide a robust solution. Therefore, correction through the use of infrastructure-based position estimation based on smartphone technology is discussed. This approach invokes the minimum cost when using existing infrastructure, whereby Pedestrian Dead Reckoning (PDR) forms the basis of the autonomous position estimation. Realizations with Particle Filters (PF) and a topological approach are presented and discussed. Floor plans and routing graphs are used, in this case, to support PDR positioning. The results show that the positioning model loses stability after a given period of time. Fifth Generation (5G) mobile networks can enable this feature, as well as a massive number of use-cases, which would benefit from user position data. Therefore, a fusion concept of PDR and 5G is presented, the benefit of which is demonstrated using the simulated data. Subsequently, the first implementation of PDR with 5G positioning using PF is carried out.

**Keywords:** indoor navigation; autonomous; infrastructure; particle filter; pedestrian dead reckoning; fusion 5G; inertial sensors

## 1. Introduction

The development of reliable indoor positioning based on Micro-Electro-Mechanical Sensors (MEMS) has been a central aim of technology researchers in recent years. Not only are such sensors cost and energy effective, but they also correspond to Mark Weiser's vision [1]; in that they work for everyone, anywhere. Thus, the objective is to develop applications that are as embedded as possible. Indeed, every smartphone— carried around by almost everyone today—can be counted as a unique source of such an application [2].

Another possibility would be 5G New Radio (NR) networks, which are expected to enable highly accurate positioning as an ideal support for sensor-based autonomous approaches. They will be available to the vast majority of the population, as is planned for 2027 in the U.K., for example [3]. The high dependency between smartphones and 5G signals seems a perfect match. Moreover, wireless radio-based communications have the intrinsic problem of signal unreliability, due to multipath effects and No Line-of-Sight signal conditions, particularly in indoor environments [4], which can be improved by using the abovementioned sensors. Inertial measurement units (IMU) are such sensors, which are not highly affected by environmental conditions; thus, many modern positioning techniques rely on their use as key sensors.

The aim is to target hundreds of location-based services while keeping humans as a central part of the system, using sensing technologies such as wearable sensors, which

have been trending in application [5]. Tracking the human pose by using virtual reality headsets, for example, is another of many examples of such applications. Many smart objects, such as watches and shoes, can also directly benefit pedestrian tracking techniques, especially in GNSS-shaded areas where there is no guiding reference.

To improve localization accuracy, prior works have generalized and fused other sources which utilize descriptive observations. The observations from different sensors, such as vision features [6,7], point clouds [8,9] from cameras, and Laser Identification Detection and Ranging (LIDAR) sensors, can be combined with odometry information to correct for drift and to provide efficient localization and tracking at the same time [10–12]. However, such vision-based auxiliary features are not always available. For instance, visual features fail in dark environments and LIDAR features fail in heavily reflective environments.

In this paper, we revisit the fundamental question: If only smartphone data (including the 5G NR network) and an environment map is provided, is it possible to localize a pedestrian for a long period of time? To achieve this, map support is not enough. Different possibilities are discussed, and it is shown that the special performance of the future mobile communication standard 5G NR plays a central role as an enabling technology. Therefore, 5G positioning, which is an infrastructure-based solution that provides absolute position information, is considered. The 5G technology is used in our final approaches, thus showing that 5G can potentially serve as a base requirement. Dense NR networks are envisioned to range from a few meters up to tens of meters; for example, assuming several access nodes per room in indoor environments [13]. Thus, 5G NR, as an infrastructure-based positioning solution, can be made available both indoors and outdoors and is an ideal way to navigate in cities (e.g., between buildings, subways, and train stations).

The remainder of the paper is structured as follows: the related work and challenges are described in the next section, section three presents the study dataset, in section four, two main positioning techniques which can work independently—that is, only smartphone sensors and a simulation for Infrastructure-based implementation (e.g., 5G)—are discussed; section five presents the autonomous position estimation method, where particle filtering map-matching is discussed; in section six, we present an initial fusion concept for the autonomous approach and 5G—which can be realized with and without taking map-matching into consideration; and finally, section seven provides our conclusions and directions for future works.

## 2. Related Work and Challenges

Over time, indoor positioning methods have evolved to the current stage, which now show an accuracy performance up to the level of one meter. However, the positioning techniques are still mostly limited to sensor error accumulation, device placements or finite labeled data. A wide range of different sensor technologies have been used in order to overcome these limits during the last few years, especially through smartphones, which have almost all the information one needs in one place. Within the available sensors in smartphones, inertial measurement units (IMUs) are in demand. This is largely because IMUs contain sensors (such as accelerometers and gyroscopes) and they provide information about the orientation and position of any object that they are attached to. However, different applications and environmental conditions influence the sensor selection and fusion type. Figure 1 shows a historical timeline of the smartphone-based positioning techniques, beginning with accelerometers.

The positioning must be accurate and reliable, even when the use of the device is varied in terms of placement (e.g., handheld or in a packet) or orientation (e.g., portrait or landscape mode). Authors in [14] have tried to combine different physics-based methods to overcome placement challenges, such as the Inertial Navigation System (INS), Pedestrian Dead Reckoning (PDR), or different filtering approaches such as the Kalman Filter (KF) for orientation tracking and the Particle Filter (PF) for map-matching. However, they could not argue that all can be done in real time applications. Therefore, open challenges and

questions can be defined clearly based on the timeline review and by aiming for a robust and real time positioning solution.
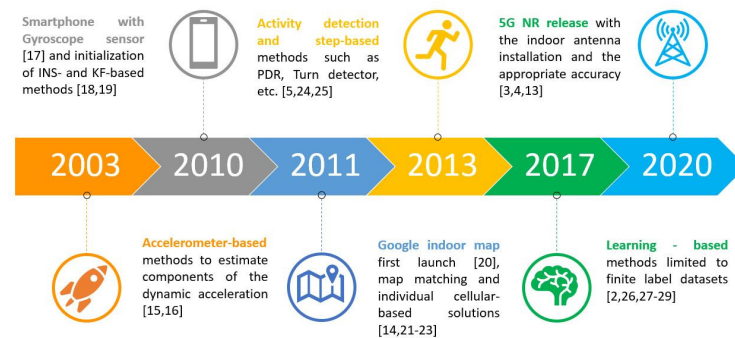


**Figure 1.** The timeline of smartphone-based positioning techniques obtained from extensive literature review [15–29].

A research challenge regarding pose tracking is how to determine the initial pose of the device. This is a very important question—if the initial position calculation is possible, then it should be also possible to estimate the new position for the next points. The pedestrian navigation should be comparable in use to GNSS-based navigation, in a way that the approach works with every smartphone in anytime. However, in order to provide high-quality positioning, absolute methods using Wireless Local Area Network (WLAN), Bluetooth, or Ultra-Wide Band (UWB) are among those individual solutions which often require big infrastructural changes, for example the additional mount of access points in fingerprint approaches [18,20,30]. GPS initialization [19] has been accepted as a standard initialization method; however, it obviously imposes a strong limit on the starting point. Manual user input is the only remaining way to start a navigation journey, perhaps by using a QR code as another specialized solution [23]. The initial orientation has fewer problems, as pitch and roll are calculable based on the gravity estimation from accelerometer measures [30]. Calibrated geomagnetic sensor measurement following a local magnetic map can also help in this process, but this is highly reliant on a labeled dataset [22].

The next challenge regards pedestrian positioning. Many studies on orientation tracking in the context of indoor positioning have attempted to estimate the heading of the device, rather than the heading of the pedestrian. They, therefore, generally assume that the position where the mobile device is attached is fixed and known, or they neglect the misalignment between smartphone heading and the user's walking direction, leaving it as an open challenge [31]. However, there have been some attempts to calculate the heading independent of orientation, either following the very first attempts based on acceleration values and PCA calculation [32], or similar approaches such as frequency domain analysis; however, such methods must be improved to reach the desired accuracy [33].

The last two challenges become even more problematic when the placement of the device varies over time as a user performs different tasks, such as making a call, carrying the device in a bag, or walking on an escalator. There are also limitless human behaviors, such as side walking, back walking, strange or jump stepping, taking stairs two at a time, and many other possibilities. Researchers have recently tried to acquired sensor data across a limited number of human subjects and smartphone placements. In this manner, the first supervised training dataset for inertial navigation was introduced in 2017, using one Support Vector Machine (SVM) and eight Support Vector Regression (SVR) models [27]. Realistic and open benchmarking datasets for pedestrian indoor positioning using modern-day smartphones together with ground-truth has become a recent research activity [28,29], employing deep learning-based approaches [2,26]. It has been found that relying on limited labeled data sources can lead to an end result. These authors did not discuss how realistic the dataset could be, due to the experimental situation; however, the question is: How can

a dataset be created, which well-represents a user acting freely, normally, and away from the experimental situation?

In order to establish an unlimited positioning approach capable of operations everywhere and at any time, as well as to find a solution for the abovementioned challenges, the potential of 5G NR technology can be considered as a key requirement. Owing to the previous popularity of smartphones for positioning estimation, 5G-based methods could be a perfect match for them. Some researchers have reported reaching an accuracy of one meter or better for 70% of the usage time different positioning measurements, such as Time of Arrival (ToA) and Direction of Arrival (DoA), in combination with Kalman Filtering [13].

## 3. The Study Dataset

This paper contributes a dataset of smartphone sensor measurements and the results of a 5G-based simulation. It also includes the required map information and interpreted Python scripts. We used a handheld Samsung S10 5G smartphone (Samsung, Suwon, Gyeonggi-do, Korea) [34], to record acceleration, magnetic field, barometer and orientation sensor values, as well as angular velocities by the gyroscope via an application named "sensor log" [35]. The simulation result, discussed in Section 4.2.2, is presented along with the building plan (in WKT format). The 5G simulator—in combination with manual video controls—was used to estimate a good ground truth trajectory.

The reader script read the sensor log file and extracted the data with desired frequencies. We solely used IMU data at 100 Hz for all of the following approaches. For the autonomous approaches, the initial point was manually set to be 566578.7 and 5932830.1 meters for the initial position and 200 degrees for initial heading. The dataset is available online at the following link (https://github.com/Hossein-Shoushtari/ElectronicsData.git) (accessed on 15 December 2020). It should be noted that the height component was omitted in the implementations.

## 4. Selection of Positioning Techniques

In the following section, two general techniques which provide position information sources are discussed. The first one only relies on sensor information, while the other just uses infrastructure measurements.

### 4.1. Pedestrian Dead Reckoning

The accelerometer–gyroscope combination is of particular interest for pedestrian dead reckoning. These MEMS inertial sensors are often combined as three-axis sensors in smartphones, such as the MPU-9250 (TDK InvenSense, Tokyo, Japan) [36]. When the smartphone is in resting position, the acceleration sensor registers acceleration due to gravity on its three axes (i.e., 9.81 m/s$^2$). This allows for tilt calculation of rotation in the smartphone–sensor coordinate frames. Step detection is also based on the registered acceleration. The three-axis gyroscope registers angular velocities. With appropriate time measurements, the relative angles of rotation in space can be determined by integration. The inertial sensors are subject to colored noise, which is even more apparent in MEMS. This can be seen in the angle of rotation, due to drift. The temperature dependence also has a great influence. These effects produce an increase of positioning error along with time of use in PDR. Therefore, the fusion of gyroscope data (drift in angle) and acceleration data (high noise in angle) helps to reduce uncertainties for two or three orientation parameters. For instance, Gyroscope and Acceleration sensor fusion has been made possible by means of the well-known Madgwick algorithm [37].

The basis of PDR is the combination of a pedometer, known or estimated stride length, and orientation. There are numerous implementation examples for the realization of the PDR, in which the positioning—both in terms of step detection and heading estimation—must be accurate and reliable. Once a step is detected, the system needs to estimate the stride length. The stride length of an individual can vary significantly over time, due to speed, terrain, and other environmental constraints [25]. The same problem applies to

the exact heading direction for each step, despite the fact that the phone can be located anywhere on the body. Using the benchmarking methods from [21] and [25], two different PDR realizations were reproduced (see Figures 1 and 2). These figures show the results of a real trajectory dataset in a building of HafenCity University.
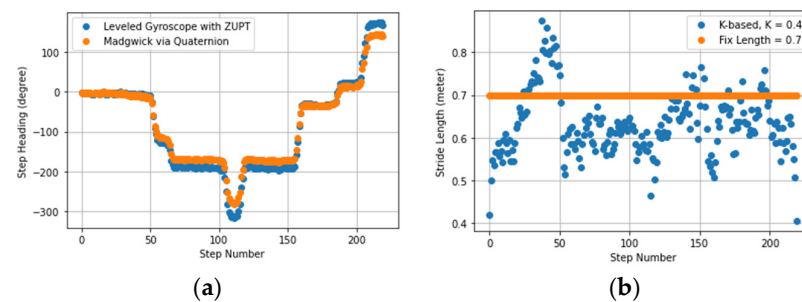


**Figure 2.** Realization of PDR elements reproducing available benchmarks, listed as: (**a**) Step heading calculation using Madgwick fusion of IMU and leveled Gyroscope considering ZUPT; and (**b**) K-based stride length estimation.

Figure 2 shows the use of Madgwick fusion of IMU data to azimuth, implemented using a Euler free quaternion-based method and the integration of gyroscope data through ZeroVelocityUPdaTe (ZUPT: Offset of rotation rate to Zero at standstill) at the beginning. Based on both of these examples, a difference of more than $20°$ is visible; however, these results are based on the same data. They make it clear that the selection of orientation estimation method has a significant influence on position estimation. However, one disadvantage of Euler based systems is the singularity limitation.

Stride length estimation based on accelerometer data works dynamically and there is no need for manual input, in comparison with the use of a fixed stride length. Based on the experiments, the k-based method generally works better for different users without changing the set of parameters. However, a variation of 20 cm in stride length between two individual's strides in a building is unrealistic. Moreover, the correction of a fixed stride length can be done more easily and quickly. The reliable determination of stride length requires a realistic dataset and learning approaches. Therefore, it can be still be seen as an unsolved challenge. In [21], the authors concluded that a fixed pre-estimated stride length causes the same deviations for an individual as the k-based methods.

The next question regards the pedometer. The authors in [38] used a query of two successive conditions for the pedometer. For this, $g$ with 9.81 m/s$^2$ had to be subtracted from the levelled accelerometer data and two thresholds for the acceleration value and one for the time were used. Other similar threshold-based pedometers have been presented in the literature (see, e.g., [25]). However, the robustness of the step detector methods remains questionable. The aforementioned reference assumed that people generate a periodic acceleration signal only when walking and could not distinguish between a real step and actions that generate very similar acceleration signal patterns, such as shaking the smartphone [30]. This may pose considerable problems, considering human daily behaviors such as walking on stairs, standing, sitting, sending texts, making calls, and typing. We seek to resolve this challenge by considering both horizontal and vertical displacement in the fusion concept introduced in Section 5.

Finally, PDR is then performed for each detected step. In Equation (1), the coordinates of the current position $X_i$ are calculated, depending on the previous position $X_{i-1}$, summing with a multiplication of the scalar translation of T (stride length), and heading matrix R.

$$X_i = X_{i-1} + T \times R \qquad (1)$$

The two PDR realizations led to different trajectories (see Figure 3). The trajectories were both subject to significant orientation drift and scale errors caused by incorrect stride

length estimation. In order to evaluate and track the approaches quality on-board, a cumulative distribution function (CDF) plot was placed next to each of the estimated trajectories. The CDFs were calculated by fitting a normal distribution to distances between the ground truth step coordinates and the estimated one, i.e., errors. In other words, the error is defined as the nominal value minus the estimated value. If there was a contrast between the pedometer and the actual number of the steps, a simple interpolation reduced or added a few step positions. The evaluation of the PDR methods shows that additional information is needed for map consideration and more accurate orientation and stride length estimation. The CDF presents the deviation qualitatively and quantitively, for instance, it can be seen that 90% of the calculated points in PDR 2 had an accuracy which was better than 15 m.
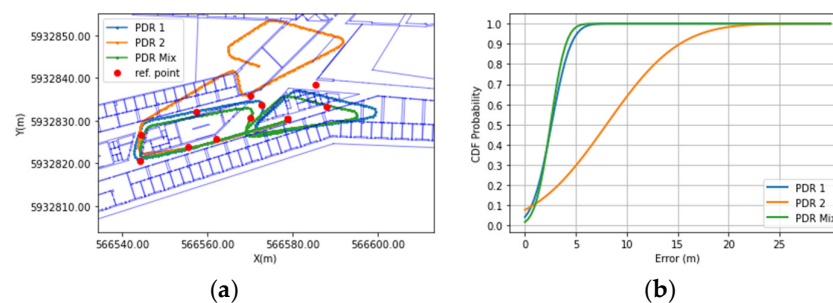


(a)        (b)

**Figure 3.** Three different PDR realizations, named PDR 1 (the k-based stride length and Madgwick-based heading), PDR 2 (fixed stride length and leveled gyroscope heading), and PDR mix (the k-based stride length and leveled gyroscope heading): (**a**) Trajectories shown on the map; and (**b**) Error vs. CDF probability of the methods.

### 4.2. 5G-Based Positioning

The deployment of cellular systems, from the First Generation (1G) to the current (Fifth Generation, 5G, or New Radio, NR) stage, has a long history. The Third Generation Partnership Project (3GPP) releases have attempted to answer the discovered requirements. The 3GPP unites seven standard telecommunications development organizations. Their members produce reports and specifications that define 3GPP technologies, including radio access, core network, and service capabilities [39]. After a while, the demand on cellular networks came not only from mobile phone providers, but also wider industry. Furthermore, 4G systems have incorporated significant updates addressing markets different than traditional mobile phone businesses [40]; for instance, the device-to-device (D2D) paradigm allows devices to directly communicate with each other using a local wireless channel. D2D technology laid the foundations for the vehicle-to-everything (V2X) technology introduced in 3GPP Release 14 [41]. However, the 5G network is the first cellular network that was not designed with a sole focus on mobile phones.

Toward the latter part of the 2010s, the last-generation networks began to reach their limits. The reasons for this were manifold, including a tremendous growth in smartphone penetration and an increase in bandwidth-hungry applications, as well as the large number of connected devices. All of these new requirements were gathered and the 3GPP initiated the definition of the 5G technology. The 5G NR requirements have been structured under three main categories [40]:

- Enhanced mobile broadband (eMBB), the aim of which is to provide wireless connectivity with very high bandwidth.
- Massive machine type communications (mMTC), providing connectivity to a large number of IoT devices, such as smart meters, watches, or wearables. mMTC requires very large cell and network capacities.
- Ultra-reliable low latency communications (URLLC), targeted at providing low latency, robust communication links for V2X, remote surgery, and other safety-critical applications.

The 5G network also includes other devices and use-cases, referred to as industry verticals. Another significant difference, with respect to previous cellular networks, is the use of higher frequencies in the millimeter-wave spectrum, starting at 24 GHz. Important features have also come from 5G, such as massive multiple-input and multiple-output (MIMO), beamforming, cloud computing, and network virtualization. All of these features, introduced in Releases 16–17 [42,43], help to increase the scalability and modularity of the network and aid in reaching peak data rates of 20 Gbps with very high user density [40].

### 4.2.1. Algorithms and Technologies

We have classified the 5G-based positioning approaches based on their geometric bases, analyzing proximity-, distance-, angle-, and time difference-based positioning technologies. In this classification, there is no consideration of the data driven approaches such as the well-known Fingerprinting method.

Proximity is the simplest way to determine the location of an object. It is a method which has been long used in cellular networks; for example, in cell ID (CID), Wi-Fi, and Bluetooth positioning systems. Proximity is based on the knowledge that the object to be located is near a reference object whose position is known. Hence, the accuracy of proximity as a positioning method basically depends on the range of the signal used. For instance, dense 5G networks, which are envisioned to range from a few meters up to tens of meters, have shown acceptable accuracy performance when using proximity [13]. The point representing the position of the mobile terminal can be obtained by geometric calculations, for which the centroid method is the most common [44]. The weight of each Antenna Node (AN) is proportional to its Received Signal Strength (RSS) value; as a result, the AN with the highest RSS pulls the centroid most strongly to its own position [45]. The same weighting analysis can be performed using time measurements. However, power measurements are not as accurate as timing measurements in the positioning technologies used in legacy cellular networks (up to LTE). This problem has been solved in 5G NR [40].

Triangulation is a technique which determines the position of an object by measuring the angles to the object from known points. It relies on Angle of Arrival (AoA) measurements, in which the incoming angle of the received signal is known, such that the receiver can estimate the direction of the transmitter. At least two angle measurements from two different known points are sufficient for 2D localization, by applying trigonometric identification. Although angle-based positioning technologies are not new, due to the beamforming feature, it is with 5G NR that their full potential can be reached. DL-AoD and UL-AoA are two 5G angular positioning technologies that are always linked to a base station beam by 3GPP specification (38.305) [46].

Trilateration is the name given to positioning algorithms referring to a position determined from distance measurements. These are also called range measurement techniques. In Trilateration, the "tri" stands for the (at least) three fixed points that are necessary to determine a 2D position [47]. In [44], the use of the least square method to minimize the localization error was discussed, where the absolute distance error between the transmitter and receiver should ideally be zero. Positioning based on trilateration can be performed using several different positioning measurements, such as Time of Arrival (ToA), RSS, and so on. Enhanced Cell ID is a method based on a proximity algorithm for LTE as an enhancement of a timing advance procedure. The aim is to reduce the area of uncertainty of the positioning [48–50]. Alternatively, if the transmitted power is known, the RSS can be used to estimate the distance the signal has travelled, by using particular propagation models that estimate the attenuation of the signal in relation to the travelled distance. This is due to the fact that the power of the transmitted signal decreases with the travelled distance [44]. In 5G NR, the Round-Trip Time (RTT) to a neighbor cell has been used to define a multi-RTT method. The NR E-CID is also a re-definition of ECID; this time, for 5G networks [40].

Multilateration refers to positioning algorithms based on the difference in distances from the object to two reference points of known location. In particular, they rely on Time

Difference of Arrival (TDoA) measurements. In general, at least two measurements (from three transmitters) are needed to obtain a 2D position, while at least three measurements are required to calculate a 3D position. In 5G NR, DL-TDOA and UL-TDOA are based on the same principle, where the time difference measurement is carried out by the network of base stations [40]. A similar method is the 4G OTDOA.

### 4.2.2. 5G Simulation

Regarding 5G, positioning methods can generate coordinates with a pre-defined resolution, accuracy, and latency. Performance varies in 5G-based technologies and 3GPP releases. For instance, in Release 17, the aim was to generate a horizontal positioning precision of at least 1 meter or higher for industrial use-cases; for example, an accuracy of 0.2 meter is desirable in some indoor use-cases. A positioning latency of less than 100 milliseconds is also desired [43]. Although a real 5G Campus Network is going to be built in the framework of the Level 5 Indoor Navigation (L5IN) project running at the HafenCity University, an indoor cellular-based positioning simulation was designed to evaluate different antenna placements, network resolutions, qualities, etc.

We carried out a simulation based on the points discussed above relating to 5G positioning methods and considering the 5G releases. However, simulation points were derived for simplicity in the following experiments, mainly by using the floor plans and reference points with random errors in a range of 5 m.

## 5. Autonomous Position Estimation

In the following section, the most promising approaches for autonomous pedestrian navigation are presented and discussed. For better understanding of the results, the technical details are also explained.

### 5.1. PDR Particle Filter

The autonomous position estimation was initialized by the PDR 1. PDR-based approaches require correction for pedestrian navigation, in the case of longer-lasting position estimations. Therefore, the available components for navigation were considered; the floor plan and the routing graph. These were intelligently combined with the PDR using PF algorithms, which has been used previously in [38].

In this variant, the PDR represents the Propagation process, and the pedometer controls the computation rate. During the estimation step, the floor plan and the routing graph were used as correction parameters. Figure 4 graphically represents the processing of the available data to determine corrections. In Figure 4a, the floor plan is used with a Boolean logic principle: If a particle is behind a wall, change its weight to zero (red). The other particles change their weights, based on their orientation with respect to the wall position (grey to black particles). As Figure 4b shows, the weighting principle was only based on the routing edges. The orthogonal offset has been used as the weight defined on the normal distribution in Equation (4).

$$\tan a_i = \frac{y_i - y_m}{x_i - x_m}. \tag{2}$$

$$w_i = \exp\left[-0.5 \cdot (\alpha_i - r_{wall}) \cdot R_r^{-1} \cdot (\alpha_i - r_{wall})\right] \tag{3}$$

$$w_i = \exp\left[-0.5 \cdot \left(d_i^{orthogonal}\right) \cdot R_d^{-1} \cdot \left(d_i^{orthogonal}\right)\right] \tag{4}$$

Equation (2) shows the calculation of the course between actual particle i and weighted mean value of last estimation step. This angle was used to compare the orientation of walls around this particle. The grey-scaled color of particles in Figure 4a shows the weights based on these comparisons to nearest wall included in a probability density function which represents a normal distribution Equation (3). Equation (4) shows here the probability density function, which represents a normal distribution. A longer distance to routing

edge produced a lower weight for this particle. The weighted mean value out of all particle moved more to routing edge, based on the idea, that this was the typical area of walking. At the end, these corrections generate a trajectory which is positioned more near routing edges, which are typically oriented in the mean axis of corridors.
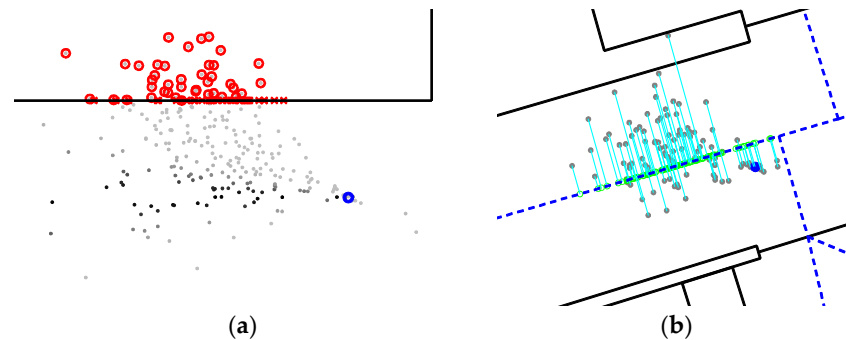


**(a)**　　　　　　　　　　　　　　　　**(b)**

**Figure 4.** Principles of support: (**a**) floor plan—red particles are behind wall and are weighted zero; and (**b**) routing graph—the orthogonal offset of a particle to the nearest routing edge is used to calculate its weight [21].

Using the approach of map support on the test data yielded a significantly different trajectory, compared to the PDR trajectory. However, the approach is already clearly less effective. Without further correction using the routing graph, the filter can change the room after a certain time, depending on the noise parameters.

*5.2. Topological Approach*

In the topological approach first presented by [38], the PF is replaced by a state detection approach. A position estimation works only based on the routing graph. The idea here is that the change of priority of orientation estimation makes the PDR more robust for longer durations of navigation. An additional advantage compared to filter approaches is the clear state detection without the influence of randomly distributed parameter repeatability. A further advantage is the requirement of less computing power, compared to a PF.

The topological approach works with four state queries. These different states are necessary to handle the different error situations based on PDR influences by step length error and drift error of calculated rotation angle. The basis is a comparison of the currently calculated direction using gyroscope data and the orientation of surrounding routing edges. A selection of the appropriate routing edge is applied. This process is repeated for each step detection. Thus, the PDR runs along the most probable routing edges. One disadvantage is that it cannot assume positions freely in space.

For the test dataset was used for this approach, see Figure 5. This approach works well if the trajectory follows a clear and simple routing graph. This was not the case here and the algorithm failed after about 60% of the run (Figure 5). The trajectory could not match the routing graph and the calculate its path. Uncertainties in positioning, therefore, increase strongly if the traversed path is not well-represented by the routing edges, or if it deviates strongly.
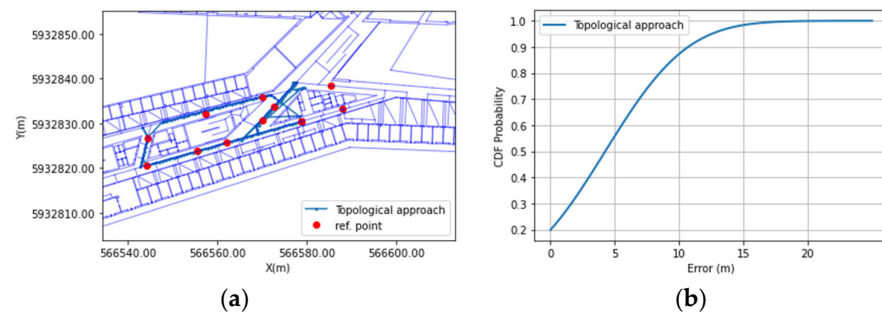
**Figure 5.** The topological approach: (**a**) The trajectory, including the route graph; and (**b**) Error vs. CDF probability of the mentioned method.

### 5.3. Edge-Based PF

The PDR PF and the topological approach both have advantages in processing the available information; however, both methods also have weaknesses. Therefore, an approach which combines both methods is needed to generate further improvement. This approach, called edge-based PF and first presented in [21], essentially represents a PF in which each particle is processed according to the topological approach. The particle, therefore, consists not only of the coordinates and the particle weight, but also a direction $r_i$ and a currently assigned routing edge, $ID_{edge}$. Furthermore, the particle weight is calculated by comparison of $r_i$ with the identified surrounding routing edge $ID_{edge}$. The $r_i$ is mainly defined by the integrated rotation rate around the vertical axis, but corrected by the use of routing edges in the PF. Based on comparisons of $r_i$ to routing edges around each particle, the next routing edge is selected. On this selected routing edge, the topological approach (PDR) is used to estimate the trajectory.

The working principle of the filter process is shown in Figure 6. When looking at the figure, the value added by combining both approaches is clear. The basis is the topological approach, which was calculated separately for each particle direction. Thus, each particle could obtain a different state from the PDR propagation. Compared to the simple topological approach, many paths could be followed in parallel through the PF. Additionally, it was possible to decouple the particles from the routing graph. This helps the filter to follow the real path better, especially in large open areas. In the realization, a threshold was used for uncoupling and recoupling to routing edges. In this paper, a 15° difference in orientation to the routing edge was used, if no other routing edge nearby was usable.
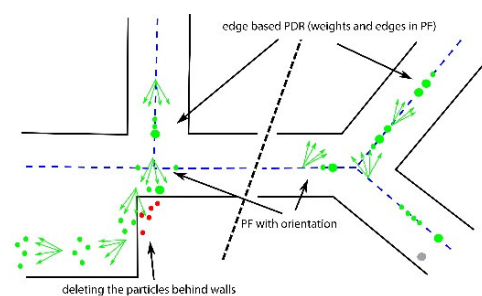


**Figure 6.** Graphical concept of edge-based PF [21].

To obtain a most likely position from the PF, the particle weights are needed. These were calculated by the difference between the orientation $r_i$ and that of the selected routing edge. Based on the particle weights, the weighted average was calculated in PF; however, it has to be additionally considered that different paths have to be estimated at the same time and where the particles are distributed. Therefore, local particle groups must be calculated. When applied to the comparable dataset used in this paper, a similar problem as with the topological approach arose (Figure 7). However, a route was mapped

to the followed path. It shows the best result of the autonomous variants presented so far. According to the CDF graph, 85% of trajectory errors were smaller than 5 m.
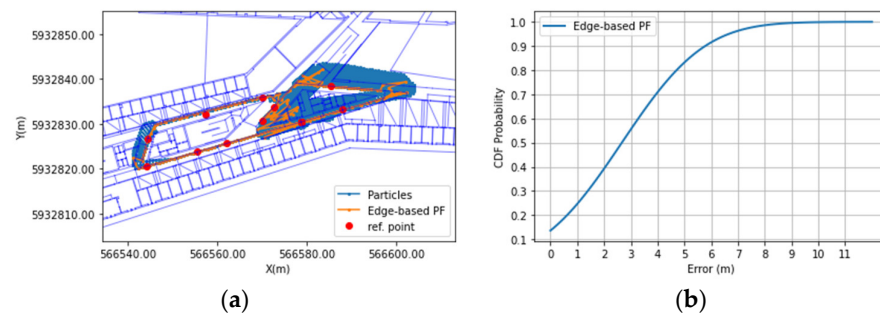


**Figure 7.** Edge-based PF: (**a**) The trajectory, including the route graph; and (**b**) Error vs. CDF probability of the mentioned method.

*5.4. Discussion*

It can be observed so far, that if the user is assumed to judge indoor navigation according to the standards of GNSS-based navigation, the approaches presented here are not yet sufficient to guarantee an equivalent position estimation in building interiors. Moreover, the autonomous variants show weaknesses that become apparent in the test dataset. The respective corrective measures do not intervene permanently or generate unpredictable routes depending on the building geometry. However, the results demonstrated that, over a certain period of time, sufficiently accurate position estimation was possible for each of the variants presented so far. This was mainly due to the quality of the coordinates obtained from the PDR and the exactly known initial information. Therefore, a hybrid variant, with the additional use of an infrastructure-based approach makes sense. A position estimate that is not always (sufficiently) accurate can be optimized using the autonomous variants presented so far.

## 6. Fusion of Autonomous Approach and 5G

The above presented approaches for autonomous pedestrian navigation all became inaccurate after some time. However, the infrastructure-based position estimation can support the accuracy requirements for a long time. The following approaches are based on the use of the 5G simulation.

*6.1. PDR and 5G*

PDR methods are classified among relative positioning approaches, in that they need an initial point. The initial point includes the position coordinate and the initial heading. In offline mode, the initialization should be done manually; the rest can be done as usual. As can be seen in Figure 8, the PDR calculation can be done at any time. The initial position point can also be obtained using 5G signals, while the initial heading can be considered as a rough first guess. Once the second 5G signal is calculated, the heading can then be corrected. During such correction, step elements can be tuned by use of infrastructure positioning. More accurately, PDR methods can be highly drifted by two main factors: The stride length calculation and the heading drift. Using parameters calculated from the 5G signals, these kinds of errors can be withheld. There is also a possibility to check whether the step counter is working well, by considering the horizontal and vertical displacement. Once a new 5G coordinate is obtained, stride length and heading correction can lead to accurate PDR, even over very long periods of time. For better visualization, the last steps can be also corrected, based on the new 5G signal.
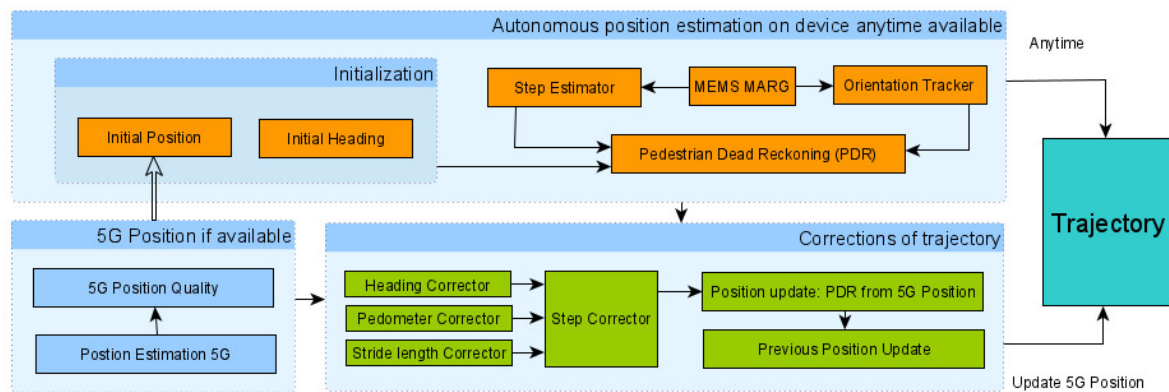
**Figure 8.** The fusion concept of PDR and 5G in both online and offline modes.

The concept of PDR with 5G correction is clarified in Figure 8. The combination allows to take the benefit of PDR, i.e., short-time accuracy, and that of the 5G positioning, which is not drifting over time. Moreover, it can be seen that the PDR works like a gap filler between the positions estimated by the 5G positioning methods. However, when the user is offline, the positioning should still be able to continue working.

The basis of the step corrector in the concept is a transformation. The aim would be to correct the scale factor as a stride length corrector and the orientation as the heading corrector. Moreover, thresholds for minimum and maximum human step length keep the pedometer corrector acting as a calibrator. This concept would be implemented and evaluated for a post-processing scenario. However, the principle would be the same with the complete and real time implementation.

At this point, we can discuss the expected performance of such a proposed system, as well as consider its evaluation under 5G networks with different densities. The very first implementations provide reliable results. In Figure 9, many 5G points from the simulation are shown. The CDF was calculated considering the previous position update under non-real-time calculation, as a proof of concept. According to the CDF plot, 80% of the estimated points were in range of 2 m of deviation. In the next step, we try to answer the following question: What if there are only a few antenna nodes?
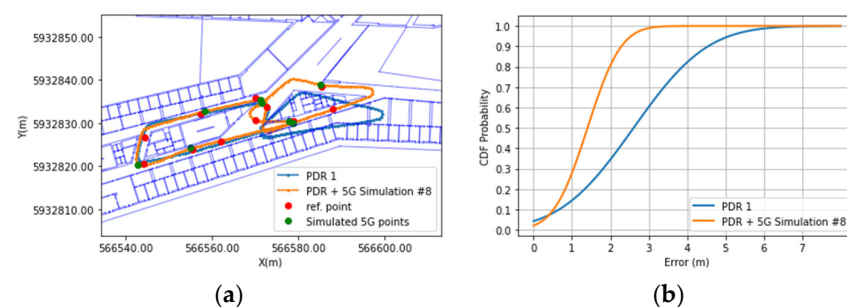


(**a**)



(**b**)

**Figure 9.** The proof of concept in fusion of 5G and PDR using eight simulated points: (**a**) Trajectories; and (**b**) Error vs. CDF probability of mentioned methods.

In Figure 10, as the path was not very long, the number of simulated points was reduced to three points. Surprisingly, there was even better performance. This effect will not be available for the real-time realization of the method. However, what happened here is that the minimum amount of the simulation points completely removed the heading drift, and there was no correction for the scale. The scale correction would be small, as the step length algorithm is working well in this experiment. Therefore, the result is nice and it illustrates how effective the concept can be. The real-time consideration and realization will be discussed in future works.
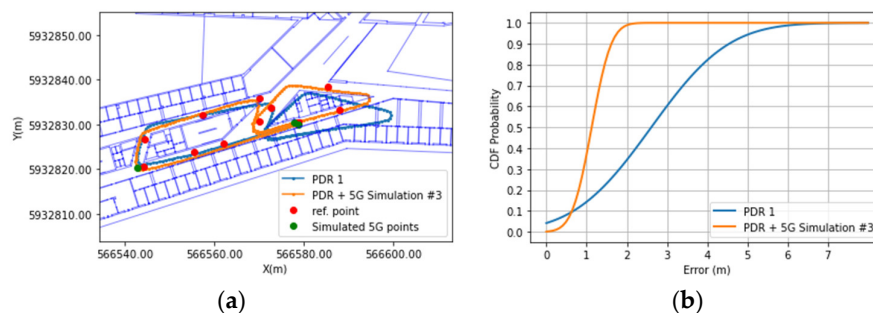
**Figure 10.** The proof of concept in fusion of 5G and PDR using three simulated points: (**a**) Trajectories; and (**b**) Error vs. CDF probability of mentioned methods.

### 6.2. Map-Matching, PDR and 5G

The fusion of autonomous methods and the infrastructure-based technologies help to find robustness, even for a long time. Using PF, the propagation was based on a PDR approach. The activation of the PF was controlled by a step detection process. A time sequence with a fixed time step was still possible. In the correction step, information of infrastructure positioning was included. Thus, coordinate differences of the estimated particles in the corresponding correction step were used as the weighting basis. Distances to known access points or proximity approaches with signal strength were also considered, through use of a probability density function. For the hybrid approach, the PDR PF with correction by ground plan data was extended by a further correction component by means of coordinate differences. Equations (5) and (6) demonstrate the weight calculation using the coordinate differences to a simulated 5G point based on normal distribution. This was coupled with the weight calculation based on the floor plan data, such that points behind a wall were still deleted. Timestamps were generated for the simulated 5G positions at the known points during the test data recording. This ensured correct time consideration by the filter.

The best result achieved so far is shown in Figure 11. The trajectory (orange) did not leave the path at any time. The critical middle area is well-bridged. The quality of this approach, however, is highly dependent on the regular availability of 5G positions.

$$d_{ij} = \sqrt{\left(x_i - x_j^{5G}\right)^2 + \left(y_i - y_j^{5G}\right)^2} \tag{5}$$

$$w_i = \exp\left[-0.5 \cdot \left(d_{ij}\right) \cdot R_d^{-1} \cdot \left(d_{ij}\right)\right] \tag{6}$$
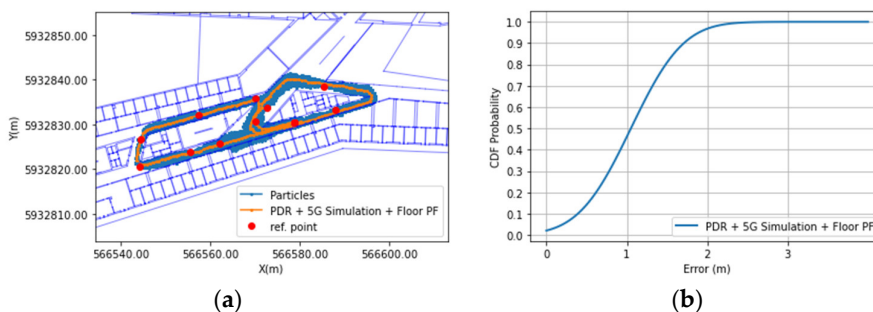


**Figure 11.** PDR PF with map and 5G simulation: (**a**) The trajectory; and (**b**) Error vs. CDF probability of the mentioned method.

### 6.3. Discussion

When combining autonomous methods with infrastructure-based methods, robust solutions were found throughout, regardless of whether filtering algorithms or the simpli-

fied method were used to estimate the position. A robust approach to position estimation for indoor pedestrian navigation is desirable. Compared to the clear navigation environment (street vectors) in GNSS-based position estimation, buildings pose particularly high demands on position estimation, due to the architectural diversity and layout dimensions involved. The hybrid approaches were able to meet these demands. Gaps in the availability of infrastructure-based support were bridged by the autonomous approach and, conversely, complex spatial structures where the autonomous approach failed were supported through the use of the infrastructure-based method. Ultimately, the two methods can be used in such a way that the stride length and orientation obtained by the autonomous variant are corrected "on the fly" by the infrastructure-based method.

## 7. Conclusion and Outlook

In this paper, different approaches to pedestrian positioning for GNSS-shaded areas were considered. By using a broad literature review including the timeline, the open challenges have been discussed. The principles for pedestrian navigation (such as "take your own device") were regarded as clear guidelines in the choice of the smartphone as the experiment device. Nonetheless, an attempt was made to estimate the position using only IMU sensor and map information; i.e., the in-demand autonomous method. In other words, the initial aim was to achieve the best possible performance by using a robust and autonomous position estimation, independent from any other individual solution such as WLAN or UWB networks which needs an app registration or a pre-defined label dataset. However, on one hand, it was concluded that a long-time localization is not fully supported by the autonomous approaches even those with functionality of the well-known map-matching methods. On the other hand, the 5G NR release (supported by 5G chips embedded in recent smartphones) guides us to the 5G-based solutions. As discussed, 5G NR can not only improve the accuracy, but also solve open challenges.

All of the abovementioned approaches were evaluated fairly by using the same test dataset in comparison with the ground truth trajectory and the accuracy performance illustrated in the CDF plots individually. By that, it was seen that the quality of position estimation increased vividly by adding support information such as map and 5G simulation, respectively. The only methods with a performance of 3 meters or better in 90% of the experiment time, were those which 5G supports. A precision of 5 meters can therefore be achieved with only map-matching techniques. These results are only valid for the published dataset, but the methods are compared together and ranked in the same environment. In summary, the collected results are shown in Figure 12. The graph also clearly shows map-matching improves performance and would be needed to model human being features which cannot pass the walls as well, for instance.
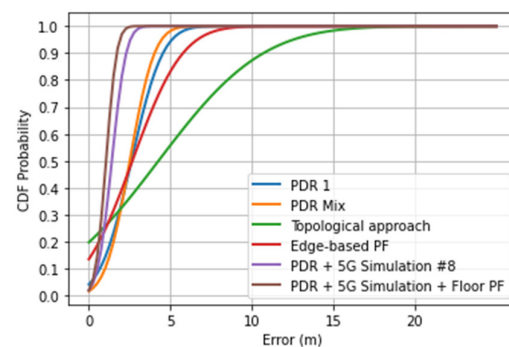


**Figure 12.** Evaluation of different implemented approaches altogether.

While infrastructure-based indoor positioning approaches usually entail high maintenance and implementation costs which must be done by facility management, the 5G, as a mobile communication generator providing various positioning technologies, does not need such support. However, the autonomous variants have weaknesses, despite

their successes, in terms of use of the existing infrastructure and individual user behavior. Nonetheless, a hybrid variant—for example the concept realization like PDR and 5G fusion, or its PF with more functionality—might be a suitable choice. The good performance of such a transformation-based correction can be seen in comparison with the other methods (See Figure 12). This research was just a brief introduction the fusion of PDR and 5G, however it opens new avenues and makes the very first experimental dataset available online using the simulation results. Moreover, the concept result illustrates promising performance, which should be realized for real time situations in the future.

Alongside data exchange inside or outside of buildings within the 5G standards, position estimation is also possible. This allows a seamless transition from indoor to outdoor areas, which will be evaluated in future works. The aim would be to show that 5G is comparable with GNSS, for both outdoor and indoor environments. It can cause faster positioning by filling the gap caused by the GNSS ambiguity resolution. Future work will be based on the realization of a 5G Campus Network in the area of HafenCity University. Moreover, different antenna placements and network configurations can be evaluated using the simulation. The combination with the available solutions based on the PDR, floor plan, or routing graph can then be based on both real and simulated data. The remaining challenges such as the limitless placement and robust pedometer can be also discussed in future works. In this work, the height component was consciously not examined. Although the height estimation is also subject to the anomalies described in this work, external corrections can help to correct the negative effects. Depending on the used technologies and evaluation methods, the problem of pedestrian navigation can be considered as either a 2D + 1D or a 3D approach.

**Author Contributions:** All authors conceived and designed the study, as well as the data collection/simulation. H.S. (Hossein Shoushtari) reproduced and designed the PDR systems and the concept of fusing 5G and PDR. He drafted most of the manuscript, with suggestions from T.W. and H.S. (Harald Sternberg), under the framework of the L5IN project. T.W. designed and implemented the PF approaches. All authors contributed to the result analysis and discussions under the supervision of H.S. (Harald Sternberg) and approved the submitted manuscript. All authors have read and agreed to the published version of the manuscript.

**Data Availability Statement:** The desired data is available in GitHub platform.

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