A COMPARISON BETWEEN UWB AND LASER-BASED PEDESTRIAN TRACKING

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ABSTRACT:

Despite the availability of GNSS on consumer devices enabled personal navigation for most of the World population in most of the outdoor conditions, the problem of precise pedestrian positioning is still quite challenging when indoors or, more in general, in GNSS-challenging working conditions. Furthermore, the covid-19 pandemic also raised of pedestrian tracking, in any environment, but in particular indoors, where GNSS typically does not ensure sufficient accuracy for checking people distance. Motivated by the mentioned needs, this paper investigates the potential of UWB and LiDAR for pedestrian positioning and tracking. The two methods are compared in an outdoor case study, nevertheless, both are usable indoors as well. The obtained results show that the positioning performance of the LiDAR-based approach overcomes the UWB one, when the pedestrians are not obstructed by other objects in the LiDAR view. Nevertheless, the presence of obstructions causes gaps in the LiDAR-based tracking: instead, the combination of LiDAR and UWB can be used in order to reduce outages in the LiDAR-based solution, whereas the latter, when available, usually improves the UWB-based results.

1. INTRODUCTION

Since the introduction of Global Navigation Satellite Systems (GNSS) modules in consumer portable devices, such as smartphones, personal positioning systems have become part of the every-day life experience of most of the worldwide population. Nevertheless, the quest for ubiquitous accurate positioning systems keeps growing, pushed by the development of new applications, for instance related to indoor positioning, or more in general positioning in challenging conditions, and by the interest in the development of autonomous vehicles (de Groot et al., 2018, Hsu et al., 2015, Zeng et al., 2017).

The interest in ubiquitous precise positioning systems motivated the recent development of a plethora of approaches for enabling accurate navigation, in particular on consumer portable devices, even in challenging conditions for GNSS. Among them, a key role is often played by vision: for instance, visual odometry has proved to be an effective solution for personal navigation in many working conditions (Nistér et al., 2004, Konolige et al., 2010, Howard, 2008, Forster et al., 2014, Gurturk et al., 2021). Effective camera-based tracking methods have also been developed, for instance motion capture systems represent dramatically accurate solutions, despite often limited to quite small areas (Moeslund et al., 2006, Mathis et al., 2020). LiDAR (light detection and ranging) based methods have also been recently considered, as shown in (Zhang and Singh, 2014, Zhang and Singh, 2017)

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Non-vision based positioning systems usually consider the integration of several sensors (Grejner-Brzezinska et al., 2016, El-Sheimy et al., 2006), typically including inertial sensors (El-Sheimy and Youssef, 2020), magnetometer (Ibrhaim et al., 2021), radio signals (e.g. WiFi, UWB) (Zhuang et al., 2016, Dabove et al., 2018, Li et al., 2018, Adegoke et al., 2019, Sakr et al., 2020), RADAR (radio detection and ranging) (Mostafa et al., 2018, Zahran et al., 2018).

When more persons or vehicles are involved in the positioning problem, cooperative methods can also be considered, usually improving the positioning performance of those not provided with good and reliable measurements for independently determining their positions (Yao et al., 2011, Alam and Dempster, 2013, Ansari, 2019, Masiero et al., 2021).

The development of effective, and independent from GNSS, pedestrian tracking systems can also be of interest in safety and monitoring applications (for instance during public events), and also for checking the social distance between persons, which has become of clear interest after the start of the covid-19 pandemic.

This paper aims at comparing the pedestrian tracking performance obtained with an UWB system, which is well known to be usable in order to obtain reliable positioning in relatively small areas (e.g. indoors), and with a LiDAR, used as static 3D laser scanner, as also considered in certain recent research works (Zhang et al., 2019, Borgmann et al., 2020, Chen et al., 2019, Xiao et al., 2016, Ozaki et al., 2012, Gidel et al., 2010).

2. SCENARIO

The test area, in the Agripolis Campus of the University of Padua, has been chosen in such a way to ensure properly working conditions for the GNSS receivers (working in post-processing kinematic), which hence can be used to retrieve reference trajectories.

Two pedestrians freely moved in the test area (see Figure 1), each of them provided with a GNSS receiver, an UWB transceiver and a smartphone collecting the UWB data. UWB positioning has been enabled by introducing a static UWB infrastructure of nine UWB anchors, visible in Figure 2, along with part of the reference pedestrian tracks (corresponding to approximately two minutes of the test).

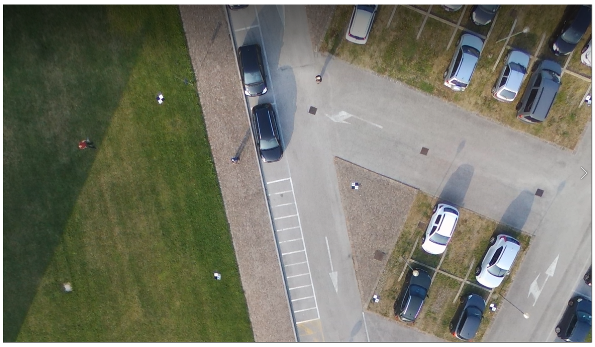

Figure 1. Drone view during the test.

The GNSS receiver was attached on a hat on the top of Pedestrian 1, hence ensuring a reasonable description of his position. Instead, Pedestrian 2 carried with his hand a geodetic GNSS receiver mounted on the top of a pole, consequently, the receiver position can be considered a reliable reference for the position of Pedestrian 2 only up to few decimeters of accuracy.

A Livox Horizon LiDAR has been installed on the second floor of a building close to the test area, and used to obtain a 3D reconstruction of the scene, during all the test duration. Despite certain occlusions caused the presence of some gaps in the detection of the pedestrian tracks, most of the test area was visible by the LiDAR (see Figure 3).

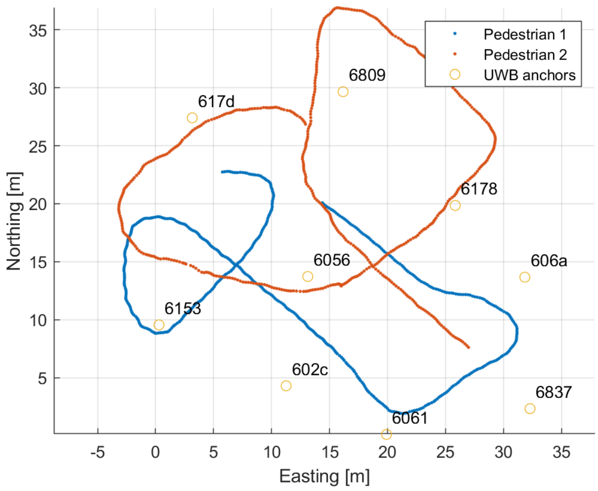

Figure 2. Example of pedestrian GNSS-based reference trajectories.

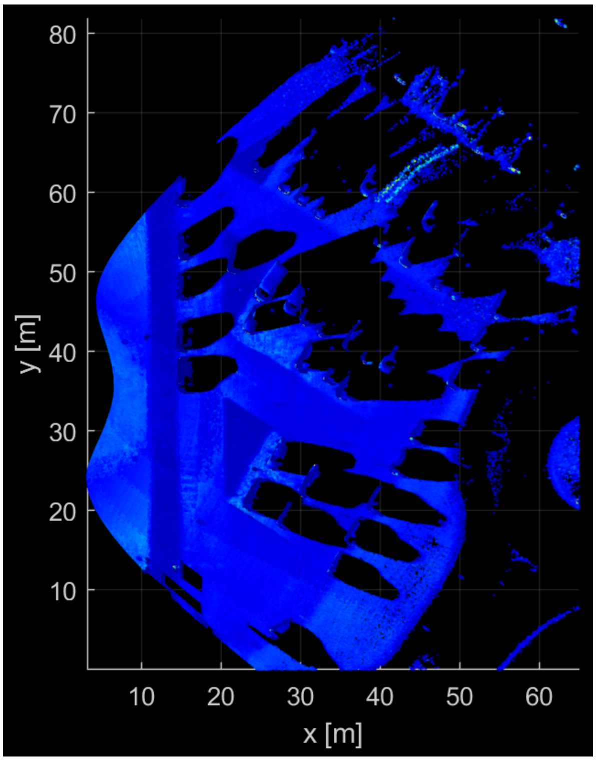

Figure 3. LiDAR map of the test area (top view).

3. METHODS

UWB-based positioning has already been recently investigated by certain of the authors: the reader is referred for instance to (Masiero et al., 2021) for a detailed description of the UWB positioning algorithm used here, in a cooperative approach fashion.

For what concerns the LiDAR-based tracking, this has been implemented through the following steps:

- First, the LiDAR position and orientation have been properly calibrated, by properly registering its measurements with certain points in the scene, measured with standard surveying instrumentation.
- An equally spaced grid has been considered on the map (Figure 3) of the test area. The side size of each cell of the grid is d, where d is a design parameter, set to 25 cm in this work.
- Let's consider a cell at time t. Then, the set S of LiDAR points, collected in a T-long time interval before t, with (x, y) coordinates falling inside of the cell are considered. $T = 1$ s in this work.
- Among the points in S, only those above the z_{min} threshold height above ground (and below z_{max}) are extracted. If the number of such points is larger than N_{min}, then the cell is marked as active at time t.
- Active cells at t form a binary map: connected components are computed on such map, and only those components with area larger than n_{min} cells are considered as moving objects/persons ($n_{min} = 4$ in this work).

- Tracking of an object/person is obtained by considering the overlaps of the object/person regions over successive time instants. Despite data association issues may in general arise (Bar-Shalom et al., 1990), this wasn't an issue in the considered part of the test.
- The centroid of the area associated to a person/object is taken as the corresponding detected position.
- Object/person tracks are re-initialized whenever obstructed for some seconds/meters.

4. RESULTS

Figure 4 shows an example of UWB-based positioning results (the trajectory corresponds to the one of Pedestrian 1 in Figure 2: the figure compares the GNSS-based reference trajectory of a pedestrian (blue), with the one estimated by means of the static UWB infrastructure (UWB anchors are shown as black circular marks).

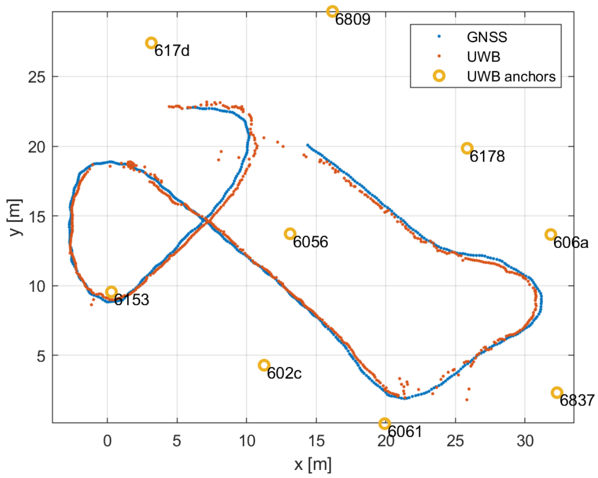

Figure 4. Example of pedestrian GNSS-based reference trajectory (blue) and the one estimated by exploiting a static UWB infrastructure (red). The reference trajectory corresponds to the blue one in Figure 2

Figure 5 aims at investigating the number of successful UWB range measurements typically available during each rover loop (the UWB rover iteratively checks, in a loop, the availability of range measurements from each of the anchors).

Figure 6 shows the probability distribution of the 2D UWB error, whereas Table 1 reports the corresponding numerical results (median and median absolute deviation (MAD) of the error).

Instead, Figure 7 shows the pedestrian tracks, corresponding to those in Figure 2, detected by the LiDAR. It is quite worth to notice that the tracks are apparently quite reliable, despite some occlusions, due to the other objects in the scene, cause some

	median [cm]	MAD [cm]
UWB Pedestrian 1	111	27
LiDAR Pedestrian 1	14	6
LiDAR Pedestrian 2	31	10

Table 1. 2D positioning results. LiDAR refers only to those time instants when the Pedestrian were detectable (e.g. not occluded).

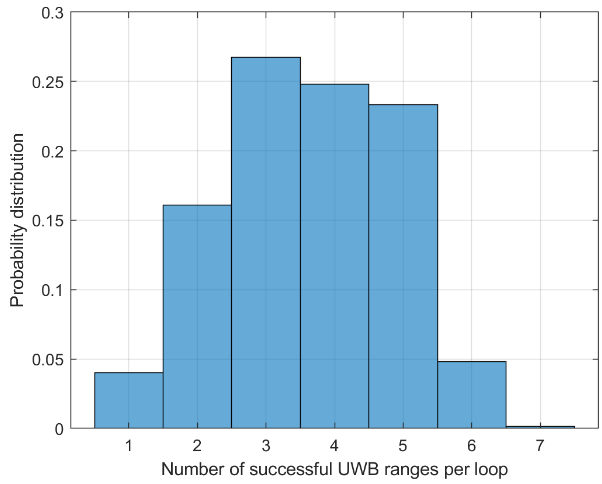

Figure 5. Distribution of the number of successful UWB ranges per measurement loop.

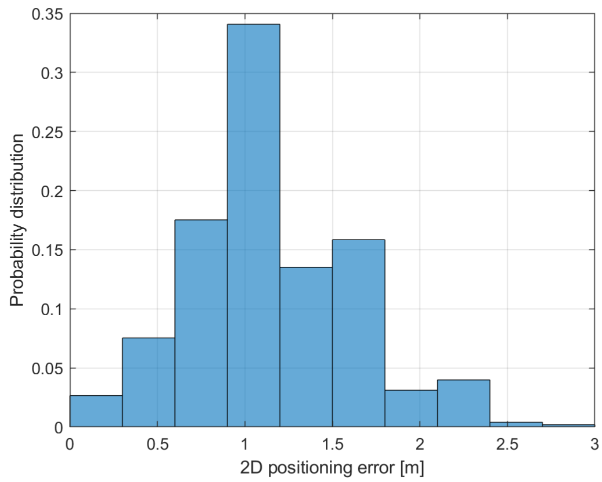

Figure 6. UWB 2D positioning error distribution for Pedestrian 1.

gaps in the tracks (on areas which are occluded to the LiDAR view).

Figure 8 shows the probability distribution of the LiDAR-based positioning error for Pedestrian 1, distinguishing between the error along the x (a) and y (b) axes. The last two rows in Table 1 report the numerical results obtained for both the two pedestrians.

If is worth to notice that both Figure 8 and Table 1 consider the results obtained only on those time instants when the pedestrians were detected by the LiDAR (e.g. they were not occluded). Nevertheless, occlusions caused some gaps in the determined pedestrian trajectories: to be more precise, pedestrians were occluded during 16% and 33%, respectively, of the considered test duration.

UWB can clearly be used in order to "bridge the gaps" of LiDAR-based positioning, and to increase the updates during all the trajectory. In this way the positioning performance during the LiDAR gaps is clearly similar to the UWB one, as shown in Table 2.

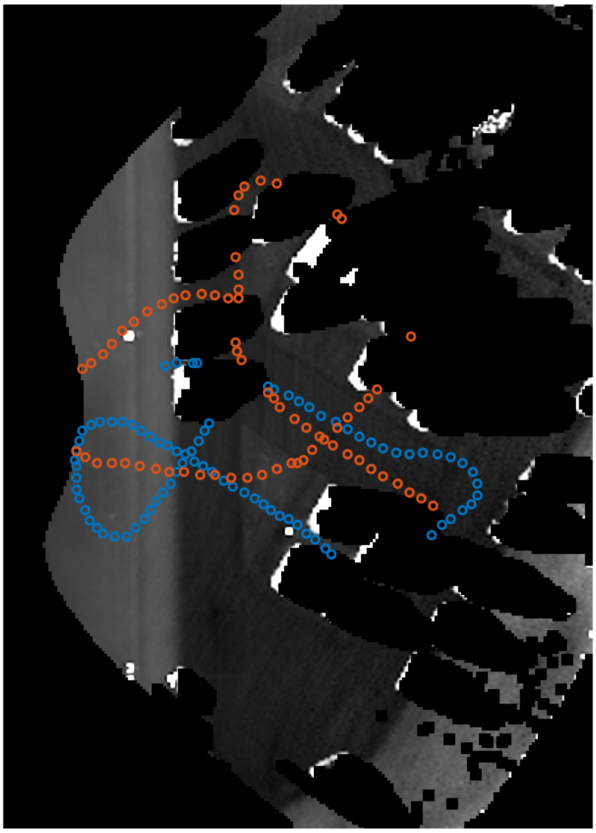

Figure 7. Example of laser-based pedestrian tracking (reference trajectories in Figure 2).

	median [cm]	MAD [cm]
UWB Pedestrian 1	119	15

Table 2. 2D positioning results obtained with UWB when the LiDAR view of the pedestrian was occluded.

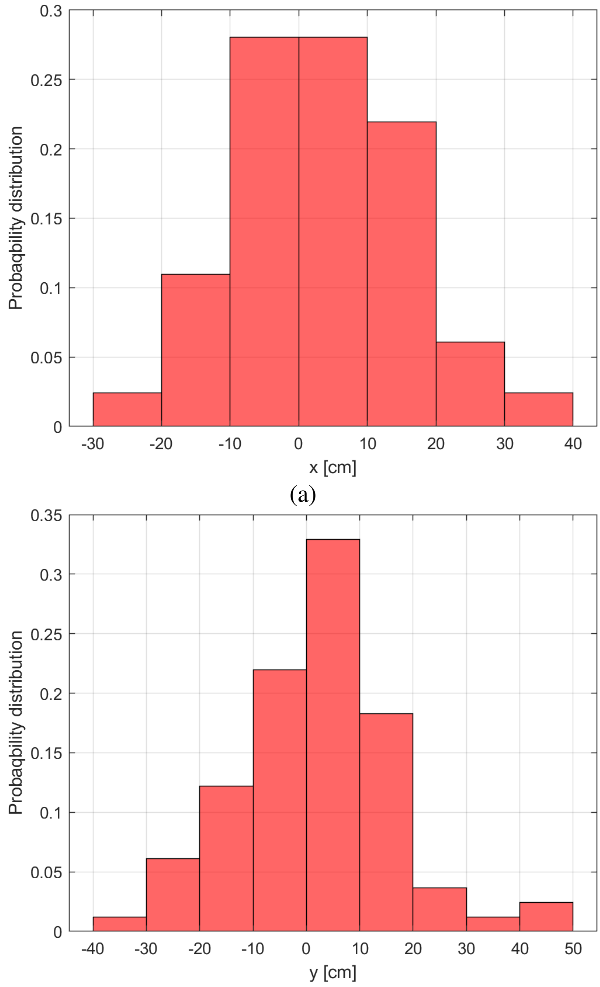

Figure 8. LiDAR-based positioning error distribution along the (a) x and (b) y axes for Pedestrian 1.

5. DISCUSSION

First, it is worth to notice that the UWB performance in this case study was below the expectations: since the average number of available range measurements were reasonably good (Figure 5), such unsatisfactory results should probably be motivated by the presence of several metallic obstacles (mostly parked vehicles), which probably negatively impacted on the quality of the UWB ranges.

The positioning results of the LiDAR-based approach are clearly influenced by the chosen cell size (25 cm). Given the value set in this work, the obtained performance can be considered as quite good, in particular for Pedestrian 1.

For what concerns the slightly worse performance for Pedestrian 2, it is also worth to notice that in this case the receiver was hand-held by the pedestrian, causing a decimeter-level error between the receiver measured position and the one typically tracked by the LiDAR (the centroid of the corresponding "blob", which usually is close to the person' head). Taking into account of such observation, the LiDAR-based error for Pedestrian 2 could be considered quite satisfactory as well.

The main issue related to LiDAR-based positioning noticed in this work was the presence of some gaps in the tracked trajectories, due to the presence of obstacles occluding the LiDAR view of the pedestrian (up to 33% of the time of the considered test duration, for what concerns Pedestrian 2).

The integration of UWB with LiDAR showed that UWB can be used to bridge such gaps, however ensuring only a degraded solution with respect to the LiDAR-based one.

6. CONCLUSIONS

This paper compared the use of UWB and LiDAR for pedestrian positioning and tracking, taking into consideration an outdoor case study, where the reference trajectories were provided by GNSS. Nevertheless, both the considered method can be used indoors as well.

The obtained results show a good positioning performance of the LiDAR-based approach (14-31 cm of median error, with median absolute deviation of around 10 cm) when the pedestrians were not occluded. However, LiDAR outage was quite significant: the presence of obstacles occluded the LiDAR view of the pedestrians up to 33% of the time of the test duration (for the second pedestrian).

The performance of UWB positioning was less satisfying in terms of accuracy, probably also influenced by the presence of several metallic obstacles (parked vehicles) in the test area, but more reliable in terms of continuity of the solution.

UWB also proved to be useful to reduce the issues related to the gaps in the LiDAR-based solution, despite ensuring less accurate results (with respect to the standard LiDAR ones) during such gaps.

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