Indoor Asset Tracking in Dense Industrial Environments Using Low-cost Wireless Technologies

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Abstract

Location based services are becoming abundant and more reliable in today's world thanks to the technological advancements achieved in the fields of positioning, navigation, and timing. Indoor asset tracking is an essential element of smart automation, warehousing, and manufacturing in industrial environments. Accurate indoor positioning systems (IPSs) exist with heavy financial costs depending on the degree of integrity required, consequently, numerous wireless based systems can be regarded as economical solutions. However, wireless positioning technologies suffer deep channel impairments especially in dense indoor venues that comprise various metallic and concrete structures. In this article, we showcase our work-in-progress research that studies a dense industrial environment in the context of indoor asset tracking. We experiment three potential wireless technologies: Ultra wideband (UWB), Bluetooth low energy (BLE) and Wi-Fi, to render a comparative assessment. Using a Multi-sensor fusion approach, we tend to complement the flaws in one technology with the merits of another, aided by physical quantity sensors like inertial motion units (IMUs). Moreover, we developed a machine learning optimization model to improve the results of the fusion based positioning scheme. The results are to be verified against millimeter-accurate reference measurements, then a seamless positioning scheme for indoor asset tracking can be achieved.

Keywords

Asset tracking, indoor navigation, wireless technologies.

1. Introduction

Modern technologies have transformed human life to new frontiers from individual and industrial perspectives. They facilitated what deemed to be inapplicable implementations from previous decades. Nowadays, new smart systems emerge on annual basis creating new opportunities for manufacturing, warehousing, and logistics.

Prior to the era of internet of things (IoT), indoor positioning and navigation became an important and vital element for Industry 4.0. Indoor positioning systems (IPSs) have seen a

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technological leap and been extensively developed since the commence of the new millennium. Moreover, asset tracking in industrial environments for people, robots, and equipment is highly dependent on reliable indoor positioning systems. Accurate and reliable IPSs come at huge initial and operating costs, consequently, other economical integrated solution have been sought. Radio frequency based technologies are promising solutions that compromise between the cost burden and performance metrics owing to their numerous advantages.

Wireless radio technologies such as ultra-wideband (UWB), Bluetooth low energy (BLE), and Wi-Fi were investigated and adopted by many industrial firms and research institutions [1]. The capabilities of wireless signals allow obstacle penetration in industrial venues, besides providing robust positioning estimations at acceptable levels of accuracy for real-time applications. However, wireless radio-based technologies suffer various channel impairments (e.g. multipath fading and interference), especially in dense environmental conditions which impose fluctuations in their performance as IPSs [2].

In this article, we present our work-in-progress research activities to cover a dense industrial environment (Technobothnia laboratory) in Vaasa, Finland. We aim to devise a reliable indoor positioning system that can support asset tracking of people, equipment, and mobile robots within the given industrial laboratory. Such venue is regularly used by universities, research institutes, regional and local corporations, and others on daily basis. Hence, a seamless positioning system will facilitate and automate numerous processes that benefit many lab visiting segments.

The rest of article is organized as follows: Section 2 describes the role of asset tracking in today's and future applications. Section 3 highlights the most important aspects around indoor positioning technologies, and introduces the potential ones to be adopted in the given context. Section 4 states the merits of utilizing Multi-sensor fusion approach to combine several IPS technologies. Section 5 focus on the role of machine learning algorithms in improving the overall IPS performance metrics. And then the Conclusions section followed by the references section.

2. Asset tracking in industrial venues

As the world approaches the fourth industrial revolution to enter the reign of internet of things (IoT) and everythings (IoE), smart manufacturing and warehousing become mainly dependent on asset tracking. Asset tracking in modern technology era is considered a backbone for smart logistics, smart delivery, smart shipping, and automated manufacturing. Industrial operators strive to keep real-time track of human resources, and robotic equipment especially inside large industrial environments. Challenging as it sounds, reliable asset tracking systems usually require higher levels of sophistication to guarantee the integrity and trustworthiness of the system. Eventually, a reliable asset tracking system could be developed at higher financial costs, in addition to compromising other performance metrics e.g. robustness, availability, scalability, and integrity.

In this article, we investigate some potential wireless technologies that could be adopted as asset tracking systems in the industrial complex of Technobothnia laboratory, Vaasa, Finland. Such dense industrial venue contain large-sized metallic structures comprising wall, tables,

Figure 1: Technobothnia laboratory, a dense industrial environment situated in Vaasa, Finland.

chairs, machines, and tools, besides other materials as concrete walls, wooden structures, etc. as shown in Figure 1.

3. Indoor positioning technologies

Indoor positioning and navigation are essential factors for asset tracking in industrial venues. Prior to building reliable indoor navigation systems, a reliable positioning technology should be identified, investigated and assessed. There exist numerous types of IPSs such as: light-based systems e.g. LASERs, RADAR based systems, ultrasound-based systems e.g. collision avoidance sensors, radio frequency based systems e.g. RFID, ZigBee, Wi-Fi, UWB, BLE, etc. All IPS technologies variate in terms of performance and feasibility, there is no single solution that fits all applications simultaneously, rather, IPS technology adoption is application-wise dependent.

For asset tracking, it is mainly concerned with personnel and robots. The tracking of humans should not necessarily be precise (sub-meter level of accuracy), rather, it is acceptable to get 1–3 meters error as fingerprinting technologies usually provide. However, for mobile robots and movable equipment, precise positioning is very important for real-time tracking due to the sophisticated responsibilities that are carried out by those machines. In this article, we investigate three potential wireless technologies that are fitting with the given environment. We selected UWB as precision positioning technology for robot tracking, in addition to BLE and Wi-Fi for human resources tracking.

3.1. Ultra wideband

UWB emerged as a precise positioning technology that can provide robust sub-meter accuracy suitable for real-time applications and personal area networks (PANs). It is a short range

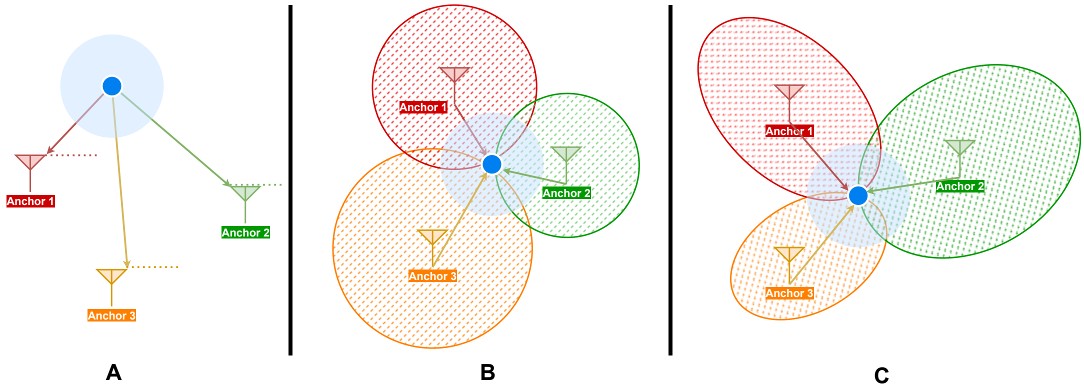

Figure 2: Positioning techniques. a) AoA, b) ToA and RSS and c) TDoA. In AoA, ToA and TDoA techniques, the user position (blue dot) is estimated from the intersection of the lines, circles and hyperbolas, respectively.

communication system with relatively short pulses that can enhance the signal penetration ability into light obstructions [1]. Moreover, UWB has a very large bandwidth (that is the reason for the term "ultra wide") spanning 3.1–10.6 GHz which provide higher capacity and data rates. The power consumption of UWB is relatively lower than most IPS technologies, which leverage the system with longer battery life and less electrical burden [2, 1].

UWB indoor positioning system comprise the use of anchors and tags transceivers, a minimum of three anchors and one tag is required for positioning [2, 1] in order to solve the positioning equations (three unknowns). A positioning technique should be defined and embedded in the system to perform the positioning process. Most commonly used techniques are: angle of arrival (AoA), time of arrival (ToA), time difference of arrival (TDoA), and the received signal strength (RSS) [3, 4]. The working principle differs depending on the positioning technique being used, eventually the positioning solution is obtained after applying selected estimation algorithms based on the formed geometrical shapes between all active anchors and the user tag, as shown in Figure 2.

In UWB, there exist numerous implementations of the mentioned positioning techniques such as: AoA, ToA and TDoA, however, the most commonly used techniques is the ToA. An approximated equation for 2D positioning estimation based on ToA is presented in Equations 1, as follows:

$$d_i = \sqrt{(x_i - x_k)^2 + (y_i - y_k)^2} \tag{1}$$

Where d_i is the measured direct distance between anchor i and the user tag, x_i and y_i are the Cartesian coordinates of the fixed anchor i, and x_k and y_k are the Cartesian coordinates of the estimated user tag x-y position at a given time instant k, where $i = 0, 1, 2, 3, ...$

Some commercial manufacturers develop all techniques in a single UWB chip. Depending on the system vendor and the given environment, UWB range for coverage could reach up to 30 meters, and the positioning accuracy can be within 2–50 centimeters in many cases [1].

3.2. Bluetooth low energy

BLE positioning technology was recently adopted by many IPS vendors for indoor applications e.g. smart homes, and smart logistics. BLE radio frequency system operates in the 2.4 GHz band, with close proximity to the Wi-Fi frequency standards. Moreover, BLE positioning is known with providing less power consumption, and more positioning accuracy in most cases [5].

Similar to UWB, BLE positioning system consists of Bluetooth anchors which in this case are called ”beacons”, in addition to a BLE user tag. However, BLE positioning is most commonly known to be dependent on RSS measurements to infer RSSI (RSS index), which is used to solve the final positioning solution. Translating RSSI into metric distance can be achieved via many approximating formulas, one of the commonly used formula is Equation 2, as follows [5]:

$$B_k = B_0 + 10\alpha log(d_k) + X_\sigma \tag{2}$$

Where B_k is the measured RSSI at a given k time instant, B_0 is the measured RSSI at the reference distance (one meter), α is the medium path loss exponent, d_k is the estimated distance in meter for a given k time instant, and X_σ is a random variable with standard deviation σ that represents a white zero-mean Gaussian noise.

The typical range of BLE technology is estimated to be between 0−25 meters, some researchers stated that BLE range could reach up to 100 meters depending on the density of the covered environment, and the positioning accuracy is within 1−3 meters in most cases [6]

3.3. Wi-Fi

Wi-Fi positioning is -by far- the most widely adopted IPS technology worldwide. Starting from an opportunistic approach, Wi-Fi access points which were primarily installed in indoor venues for Internet coverage, have been used for indoor positioning using RSS information. Later, new Wi-Fi access points were introduced as the old devices were upgraded and leveraged with positioning engines that analyze the sensed wireless signal attributes to provide fingerprinting solutions [7].

Similar to BLE, the working principle of Wi-Fi based positioning is centered around the RSS/RSSI information received from mobile devices and their MAC addresses, then, the positioning algorithms (e.g. Equation 2) provide the most-likely user position estimation [5]. The typical range of Wi-Fi positioning systems depends on the ranges of the utilized access points, also the typical positioning accuracy can be within 1−10 meters depending on the density of the given environment [5].

3.4. Inertial motion systems

Tracking assets in industrial venues requires additional degrees of confidence which can be obtained from retrieving more information about the moving object or person. Consequently, the use of inertial motion units (IMUs) became an effective factor in asset tracking for the extra information layer they provide. IMU sensors are physical-quantity instruments that measure the line and angular accelerations, Euler angles to infer the heading direction, and magnetism due to 3D Cartesian axes.

From a dead reckoning (DR) perspective, IMU lies at the foundation backbone of DR based positioning systems e.g. pedestrian dead reckoning (PDR). In modern IPS technologies, IMUs are most commonly used as an assisting technology to the primary IPS being used, that is, a Multi-sensor fusion approach.

4. Multi-sensor fusion techniques

Multi-sensor fusion is a computational procedure to fuse data from multiple sources in order to enrich the end-result information [8]. The concept of combining multiple IPS technologies has attracted the attention of IPS designers in order to improve the positioning resolution. As every IPS technology has its own merits and drawbacks, Multi-sensor fusion based positioning can be a key solution to minimize the overall IPSs errors. A single IPS technology could be complemented by additional IPS technologies either by loose or tight coupling schemes [9, 10].

Loose coupling integration scheme is obtained by combining the measurements of two or more IPS technologies such that no certain data source is affecting or influencing the measurements from other sources being integrated. Moreover, loose coupling is not dependent on sequencing, hence, any order of data measurements are accepted.

On the contrary, tight coupling scheme comprise the integration of two or more IPS technologies such that some data values are affected and influenced by other data sources being fused. Thus, tight coupling requires proper sequencing of data measurements i.e. place information into suitable order.

An example on loose coupling algorithm that fuses the measurements of UWB and IMU technologies is shown in Equation 3:

$$\mathbf{y} = \begin{bmatrix} d_i = \sqrt{(p_i^x - s_i^x)^2 + (p_i^y - s_i^y)^2} \\ \phi_i = \mathbf{arctan2}(p_i^y - s_i^y / p_i^x - s_i^x) \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \end{bmatrix} \tag{3}$$

Where $\mathbf{y}$ is the state-space measurement vector, d_i is the hypotenuse distance from the user to the measuring device, p_i^x and p_i^y denote the positioning states in x-y coordinates at time instant i, s_i^x and s_i^y denote the measured slant distances from UWB sensors in x-y coordinates at time instant i, ϕ_i is the measured heading angle from IMU sensor at time instant i, n_1 and n_2 are the Gaussian noise figures associated with both sensors respectively.

Then, the loosely coupled algorithm (UWB/IMU) proceeds to calculate the predicted state-space estimation of the Multi-sensor fusion solution using the discretized Euler-Maruyama Equation 4 as follows:

$$\begin{bmatrix} p_{i+1}^x \\ p_{i+1}^y \\ \phi_{i+1} \end{bmatrix} = \begin{bmatrix} p_i^x \\ p_i^y \\ \phi_i \end{bmatrix} + \begin{bmatrix} v_i\, cos(\phi_i)\Delta t \\ v_i\, sin(\phi_i)\Delta t \\ \omega_i \Delta t \end{bmatrix} + \begin{bmatrix} e_1 \\ e_2 \\ e_3 \end{bmatrix} \tag{4}$$

Where p_{i+1}^x and p_{i+1}^y are future predictions of the next x-y position, ϕ_{i+1} is the prediction for the next heading (orientation) angle, v_i is the line velocity of the moving object, Δt is the given time step, ω_i denotes the measured angular velocity by IMU, and e_1 e_2 e_3 are the normalized Gaussian noise vector per each state space estimation respectively.

The main advantage of Multi-sensor fusion approach is to resolve the drawbacks of each IPS technology by integrating with other assisting technologies, also combat the effect of data outliers that are usually caused by systematic errors or non-line-of-sight (NLOS) conditions. Another prominent solution that has been widely adopted to optimize IPS performance in NLOS situations is by using machine learning algorithms.

5. Machine learning optimizations

Outliers are those data points that are significantly different from the rest of the dataset. Inconsistency in data entry or erroneous observations can result in outliers in a dataset. Outliers are usually referred to as abnormal observations which can cause skews in the data distribution.

Although outliers are usually considered erroneous data, they may also carry some important information. Therefore, the outlier detection techniques should cope with the outliers instead of just removing them.

Outlier detection approaches can be classified based on the machine learning algorithms being used. These classifications include clustering-based approaches, classification-based approaches, dimension-reduction-based approaches, and hybrid approaches that combine multiple technologies together [11].

In this paper, we would implement these four classification approaches, then analyze and compare the results in the context of the improvement of the accuracy of indoor positioning.

The planned steps to render the machine learning-based optimization task in our study, are provided as follows:

- Defining the outlier: The data point that is unusual and differs significantly from other data points.
- Outlier detection: We will implement a machine learning model to find whether the training data is polluted by outliers.
- Novelty detection: Investigate if a new unseen observation is an outlier or not. Here, the training data may or may not be polluted with outliers and we are interested in finding whether a new unseen observation is an outlier or not. If that observation is an outlier, we refer to it as a novelty.
- Anomaly detection: We will combine both outlier detection and novelty detection.

All the models used would be trained with a percent of the observed data, then the trained models would be evaluated using the whole (100 % of the) dataset instead of only the remaining percent of the test dataset. This is essential because our task is aimed at differentiating the outlier and normal data from the whole dataset, not just part of it.

The results of the outlier detection process will be evaluated using assessment metrics such as precision, recall, F1 score, and accuracy. Furthermore, we will also evaluate the results by plotting the receiver operating character curve (ROC).

Initial evaluation of the UWB dataset collected can be seen to have very distorted data points compared to the Omron robot data points used as the ground truth. From investigation, we discovered that the data collection synchronization could cause this significant offset in the data points between the UWB and Omron robot. Applying smoothing with the Savitzky-Golay filter is used to eliminate noise in the UWB signal and improve the smoothness of a signal trend as seen in Figure 3. The filter is used to calculate a polynomial fit of each window based on polynomial degree and window size. Several window sizes were implemented as seen in Table 1. Figure 3 shows the data point route for a window size of 53.

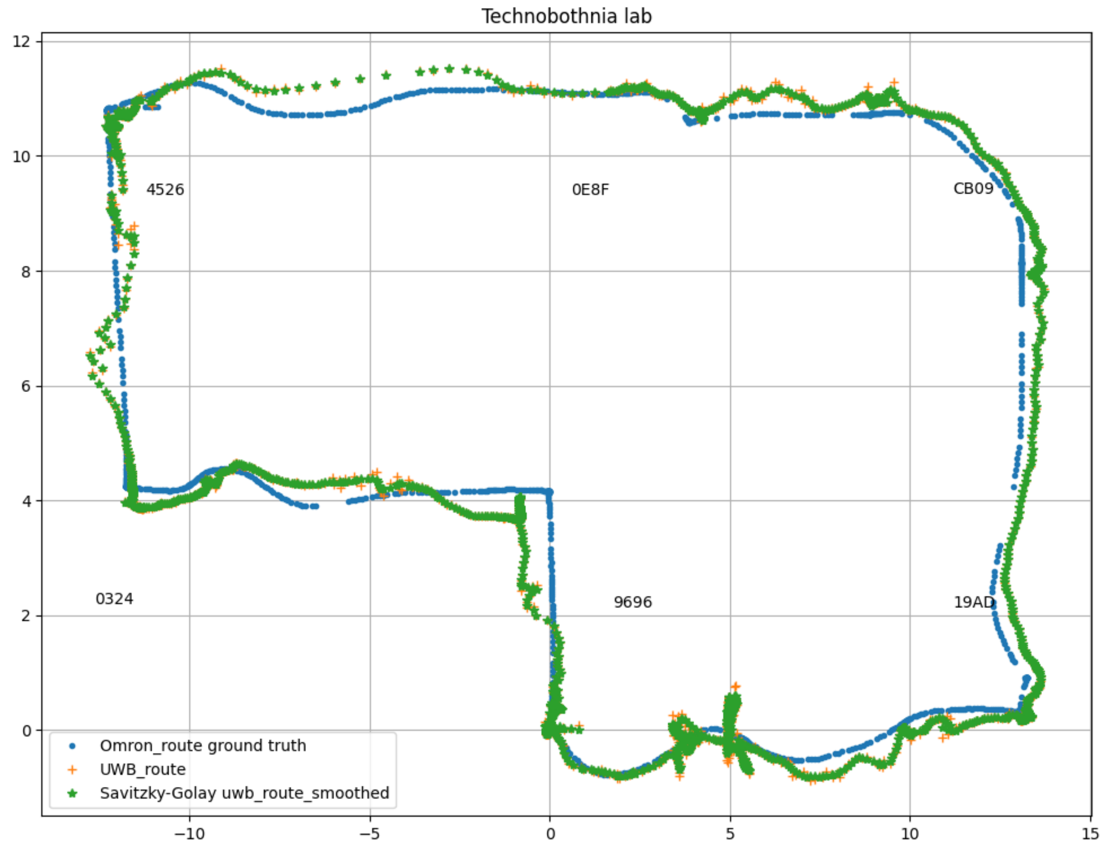

Figure 3: Indoor route in Technobothnia laboratory (Savitzky-Golay filter with a window size of 53).

The error was seen to be significant as a result of the unsynchronized data collection even after applying the Savitzky-Golay filter as seen in Table 1.

Table 1
Mean Square Error (MSE) measurement offset between the UWB route and the Omron ground truth route.

UWB route	Savitzky-Golay Smoothed UWB route			Linear regression
	window size 53	window size 63	window size 93	offset predictor
30.3541	30.3420	30.3390	30.3171	0.5253

Applying a Linear regression (LR) model to the dataset to predict the offset can help improve the error measurement. The LR model was trained on the Omron [x,y] and UWB [x,y] positions and the offsets between the Omron and UWB data points [diff X and diff Y] were used as the target. The resultant mean square error (MSE) for the LR models is 0.52527 as seen in Table 1.

The initial results look promising and we plan to implement a synchronized data collection procedure to reduce the initial offset before applying outlier detection and offset prediction ML models to improve the position estimation of the proposed indoor positioning system.

6. Integrity of indoor navigation systems

Indoor navigation systems and IPSs need to be assessed against certain performance metrics to guarantee the best quality of service and ensure security against hazardous situations. The integrity of IPSs can be described as the degree of trustworthiness that can be allocated to the received information from a given navigational system [12].

System accuracy is often perceived as the most important metric in IPSs, however, integrity culminates all other performance metrics such as: accuracy, availability, and continuity. Accuracy is the degree of matching of the estimated positioning results to the given ground truth data. And, availability is the up-time duration in which the IPS could be usable. While, continuity is the ability of an IPS to maintain the designed service level during the up-time [8].

In our implementations, we devised a Multi-sensor fusion plan to maintain all previously defined metrics, that is, to achieve an IPS with a high integrity score. In a challenging environment as the given industrial laboratory, keeping the system accuracy, availability and continuity within the desired service levels is very important as it is also very challenging. Furthermore, the hardware part of the ongoing implementation is being backed up with numerous software remedies that comprise minimized cost functions, data cleaning formulas, estimation algorithms, and machine learning optimizations.

7. Conclusions

Seamless indoor navigation is a very crucial element for various smart applications and use cases (e.g. smart logistics and IoT) in industrial and civilian sectors. The designing of integrated IPSs in industrial premises requires some sophisticated modelling for the dense environment in which the IPS is expected to operate. In this article, we briefed the reader about our work-in-progress research to develop an integrated IPS to be used by humans and mobile robots for reliable asset tracking in industrial venues. In addition to the selected potential IPS technologies, we also provided an overall view about our algorithmic toolbox to maintain high degrees of performance and maximize the system integrity.

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