Improving accuracy of indoor localization system using ensemble learning

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ABSTRACT
Recent innovations in Light-emitting diode (LED) technology and Internet of Things applications have promoted the development of visible light communication and localization applications. LED-based indoor positioning application has been a potential topic attracting the attention of many researchers because this positioning technique provides high accuracy, low cost, simple operation, and medium complexity. This paper focuses on analyzing the positioning quality with different LED layout structures. Furthermore, we consider the influence of noise in these models through the ensemble learning algorithm. We also combine the ensemble learning method with the trilateration algorithm in the proposed solution. The numerical simulation results show that the proposed solution respectively achieved a positioning accuracy of 0.023, 0.011, and 0.009 m when we considered the negative effect of all noises in 3 distinct layouts: 3 LEDs, 4 LEDs, and 5 LEDs.

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1. Introduction

Indoor positioning systems (IPS) with high accuracy and stability have been a severe challenge for scientists in recent years (Chen et al., 2019; Do & Yoo, 2015; Huang et al., 2020; Shen et al., 2020; Yue et al., 2021). The development of a wireless indoor positioning system that ensures the above technical conditions, security, and safety for people continues to be one of the issues that need to be solved more intensively (Ahmed et al., 2020; Anitha Vijayalakshmi & Nesa Sudha, 2018; Blinowski, 2015; Murai et al., 2012). To summarize and evaluate recent notable achievements in the IPS field, Germán Martín Mendoza-Silva et al. have listed the latest IPS, and the corresponding achieved accuracy as shown in Table 1 (Mendoza-Silva et al., 2019). It is worth noting that many solutions can be used for IPS systems, although the average positioning accuracy of most of the mentioned technologies is relatively poor. The positioning method using visible light is the only technique with positioning accuracy to mm level. However, the accuracy of each study depends greatly on many factors such as experimental area, number of Light-emitting diodes (LEDs), arrangement of LEDs, types of LED, optical receivers, methods of data collection and processing, etc. (Fang et al., 2017; Tran & Ha, 2020; Tran & Ha, 2021; Zhang & Kavehrad, 2013).

Recent LED-based IPS studies have demonstrated the great potential of using LEDs to develop modern indoor positioning applications with very high accuracy. In (Hong et al., 2020), the authors applied third-order regression and ridge regression algorithms to improve the positioning accuracy using quadrant solar cell (QSC). A novel feature in that paper is using QSC as an optical receiver instead of traditional photodetectors (PD) (Lin & Zhang, 2020; Sheikh et al., 2021). Besides, to improve the real applicability of IPS based on available devices such as smartphones and smartwatches, many researchers have used the built-in camera on these devices for positioning purposes. In a different approach, the authors in (Hua et al., 2021) tried to combine different types of optical sensors, including PD and Camera, to compensate for their deficiencies, hence enhancing the positioning accuracy. The experimental results showed that their suggested methods achieved an accuracy of 8.67 cm in 2-dimensional space and 12.15 cm in 3-dimensional space. In addition to sensors, the positioning efficiency depends mainly on selecting the positioning technique. To determine the location of objects in any environment, researchers can use many different methods such as Received Signal Strength (RSS), angle of arrival, time of arrival, time difference of arrival, the phase difference of arrival (Obeidat et al., 2021). Also, the use of filters to...
Figure 1. Positioning error with trilateration method.

Table 1. Recent IPS technologies (Mendoza-Silva et al., 2019).

| Technology                      | Accuracy                                                                 |
|--------------------------------|--------------------------------------------------------------------------|
| Visible Light                  | Median < 1 mm to < 2 m                                                   |
| Sound                          | Ultrasound (< 1 cm); audible sound (< 10 cm)                            |
| Magnetic Fields                | Artificial field (median < 1 m); natural field (median < 5 m)            |
| Pedestrian Dead Reckoning      | 1–10 m                                                                  |
| Ultra-Wideband                 | Median < 50 cm                                                          |
| Computer vision                | < 1 m                                                                    |
| WiFi                           | Fingerprinting (median < 2 m); other techniques (median < 2 m)            |
| Bluetooth                      | Median 2 m to 5 m                                                       |
| Radio Frequency Identification | Median < 2 m                                                            |
| Cellular                       | Median < 50 m                                                            |
| Wireless Sensor Networks       | Median < 2 m                                                            |
| Zigbee                         | Median < 5 m                                                            |

process the received optical data is a simple but quite effective approach. In (Amsters et al., 2020), the authors applied an extended Kalman filter, a particle filter, and a hybrid method to estimate locations using a camera. Besides developing algorithms to improve the positioning quality of the system, some recent studies focus on applying IPS for specific applications of which mobile robots and manipulators are typical examples (Guan et al., 2021; Guan et al., 2020; Madane et al., 2021). In (Guan et al., 2020), the authors used a turtle robot and an industrial camera to receive the optical data from 3 LEDs. Moreover, the authors also applied a loosely coupled visible light positioning (VLP) – inertial fusion to achieve a positioning accuracy of 2.1 cm and an average computational time of 33 ms in a low-cost minicomputer. In addition to mobile robots, the manipulator is also a highlight in recent studies related to IPS. In (Madane et al., 2021), the authors developed a system that was used to determine the rotation of the robotic arm on the base of machine learning. Recent promising research needs to continue to overcome the challenges that the IPS faces in natural environments and applications. The influence of multipath reflection, interference from ambient light, building structure, etc., are the main obstacles that need to be addressed (Huy & Ha, 2019). Recently, artificial intelligence (AI) has gradually become the preferred choice of researchers in many fields (Căleanu et al., 2007; Chen et al., 2005; Du et al., 2007; Han et al., 2008; Hu et al., 2012; Sun et al., 2005; Wang et al., 2010; Zhao & Huang, 2012). A similar trend is taking place in IPS-related applications (Huy & Ha, 2019; Tran & Ha, 2021). In particular, AI-based algorithms have significantly improved the positioning performance of systems using fingerprinting, the most popular technique in recent IPS studies. AI algorithms have reduced the number of markers which is one of the significant disadvantages of fingerprint-based positioning techniques (Tran & Ha, 2021). In addition, the AI algorithms also improve the system’s positioning accuracy under the adverse conditions of multipath reflection, which is also one of the challenges that cannot be easily overcome when applying IPS in practice (Huy & Ha, 2019).

In the previous paper, we presented the influence of noise on the IPS by using the trilateration method as shown in Figure 1 (Tran et al., 2021). The results obtained in that paper proved that applying the trilateration method under the negative effect of noise was not an optimal solution. In this paper, we focus on solving those problems. The main contributions of this paper are summarized as follows:

- The ensemble learning method is applied to overcome the influence of Gaussian noises and non-light of sight
channels on the positioning accuracy. The results and analyses corresponding to the cases with and without noises are presented in detail.

- In addition, we analyze the system with different LED structures (i.e., 3 LEDs, 4 LEDs, and 5 LEDs). The obtained results provide a deeper insight into this potential IPS.

The remainder of this paper is organized as follows. Section 2 introduces the overview of the VLP system and the proposed algorithms. In Section 3, we offer the simulation results and discussion. Finally, the conclusion is summarized in Section 4.

2. Methodology

In this section, we first present the overview of the suggested VLP system, then the connection between trilateration and ensemble learning methods is also given in detail.

2.1. System overview

In this section, the VLP system is described in detail. The experimental space is designed in an empty room with a standard size of 25 m² (5 m × 5 m). In this room, 10W LED bulbs are used as optical power transmitters. The LEDs are arranged as shown in Figure 2, in which we have three different layouts: 3 LEDs, 4 LEDs, and 5 LEDs. The positions of LEDs in each case are presented in Table 2. To gather data from LEDs, we use a photodetector placed on the floor, which is 2.5 m far away from the LEDs. Necessary system specifications are also described in Table 2.

We applied the VLP channel to design the IPS, as shown in Figure 3. There were three distinct parts in this scheme, including transmitter, optical channel, and receiver. In the transmission section, the LEDs played a prominent role. Their drivers controlled these LEDs and sent the optical data to the receiver side. The receiver communicated with the transmitter via optical signals. Through this channel, the receiver gathered necessary data, the all obtained data were processed to determine the final location of the mobile object.

In this work, we investigate the negative impact of various types of noise on the system’s positioning quality. Therefore, Gaussian noise types have been part of our studies. There are three main types of noise associated with Gaussian noise, including shot noise ($\delta_{\text{Shot}}^2$), thermal noise ($\delta_{\text{Thermal}}^2$), and inter-symbol interference ($\delta_{\text{Inter}}^2$), as...
shown below (Komine & Nakagawa, 2004):

\[
\delta^2_{\text{Shot}} = 2q\gamma PB + 2ql_l2B
\]

\[
\delta^2_{\text{Thermal}} = \frac{8\pi KT}{G} \eta_{PD} A_l B^2 + \frac{16\pi^2 KTF}{g} \eta_{PD}^2 A^2 l_3 B^3
\]

\[
\delta^2_{\text{Inter}} = \gamma^2 P_l^2
\]

where \( q \) and \( \gamma \) the electronic charge and PD responsibility, respectively; \( P \) is the transmitted optical power; \( l_l \) and \( l_2 \) are the photocurrent due to background radiation and the noise bandwidth factor, respectively; \( B \) is the equivalent noise-bandwidth of the PD; \( K \) is the Boltzmann’s constant; \( T \) is the absolute temperature; \( G \) and \( g \) are the open-loop voltage gain and the transconductance of FET, respectively; \( \eta_{PD} \) is the fixed capacitance of PD per unit area; \( A \) is the active detector area of the PD; \( F \) is the FET channel noise factor, and \( I_3 \) is the noise-bandwidth factor; and \( P_1 \) is the received optical power caused by inter-symbol interference.

Furthermore, the influence of ambient light and the impact of multipath noise on the positioning quality of the system are also analyzed. In this system, the optical power received from the direct and reflected channels is expressed as follows (Komine & Nakagawa, 2004):

\[
P_D = \frac{P}{2\pi h^2} \cos^n(\phi) T(\phi) g(\phi) \cos(\phi),
\]

\[
0 \leq \phi \leq \phi_{1/2}
\]

\[
P_R = \frac{P}{2\pi h_1^2 h_2^2} \rho \cos^n(\phi) dA w \cos(\phi) \cos(\phi)
\]

\[
\times \cos(\phi_{1/2}) T(\phi_{1/2}) g(\phi_{1/2})
\]

where \( n = -\ln2/\ln(\cos(1/2)) \) is the Lambertian order; \( dA_w \) is the surface element on the wall, respectively; \( h \) is the transmission distance from the LED to the PD; \( \phi \) and \( \phi \) are the angle between the transmitter and the receiver, and the incidence angle respectively; \( T(\phi) \) and \( g(\phi) \) are the gain of the optical filter and the gain of the optical concentrator; \( \phi_{1/2} \) is the receiver FOV; \( \rho \) is the reflectance factor; \( h_1 \) and \( h_2 \) are the distance and the distance and the angle between a reflective point and the receiver; \( \alpha \) and \( \beta \) and \( \phi \) (sub) \( r \) (sub) are the angle of irradiance from an LED to the reflective point, the angle between a reflective point and the receiver, and the incidence angle of the light from the wall, respectively.

From these powers, the final power was computed as follows (Figure 4):

\[
P = P_D + P_R
\]

In Figure 4a, the received optical intensity has a triangular distribution similar to the arrangement of LEDs depicted in Figure 2a. The lighting densities in specialized areas vary considerably. While the upper two corner areas are severely underexposed, the area below the optical intensity is stable and uniform. Similar results are shown in Figure 4a and c for 4 and 5 LEDs, respectively. In Figure 4c, this distribution is very homogeneous when using 5 LEDs. Therefore, these results also affect the final positioning results.

### 2.2. Proposed solution

In the previous work (Figure 5), we demonstrated that the trilateration algorithm achieved high positioning accuracy in a noise-free environment. However, the positioning error becomes worse when we consider the negative influence of noise types (i.e. Gaussian noises and multipath reflection). The appearance of indirect light significantly degrades the positioning quality because the trilateration algorithm can hardly meet the positioning requirements with high accuracy in a realistic environment. Therefore, we need to propose better solutions to help IPS achieve higher positioning accuracy.

To determine the coordinates of the moving object, we proposed a combination of trilateration and ensemble learning methods. The entire process is detailed in Figure 6.

We first gathered 1875 RSS data from the three proposed layouts (i.e. 625 RSS data for 3 LEDs, 625 RSS data for 4 LEDs, and 625 RSS data for 5 LEDs). All collected
data were divided into three main groups corresponding to each layout. Each group of training data continued to divide into ten subgroups to randomly apply the ensemble learning algorithm. Then, the support vector machine algorithm trained each subset of data. After finishing the training phase, we estimate the object coordinates thanks to the closest RSS values. Finally, we determined the final location by averaging all the estimated locations.

By applying the proposed solution, we can simultaneously take advantage of the strengths of both the ensemble learning method and the trilateration algorithm. In particular, ensemble methods improve the predictive performance using multiple SVM algorithms. As for the trilateration algorithm, one of its highlights is its simplicity and relatively good accuracy. Moreover, this algorithm is also suitable for fingerprinting method.

### 3. Simulation results

In this section, to demonstrate the superiority of our proposed approach, we, in turn, evaluate and compare the positioning quality in the three proposed layouts. Firstly, we estimated the coordinates of 125 random points using the ensemble learning algorithm without noise in all 3 cases (i.e. 3 LEDs, 4 LEDs, and 5 LEDs) as illustrated in Figure 7 (without noise) and Figure 8 (with noise). In the case of noise, we both considered the negative impact of Gaussian noises and non-light of sight channels. Conversely, in the case of no noise, we only focused on the light of sight channel and ignored the presence of Gaussian noises. In fact, the influence of Gaussian noises is quite small (Tran et al., 2021). Therefore, the influence of multipath reflection when considering non-light of sight channels is really the factor that directly affects the positioning accuracy.

Furthermore, the Cumulative Distribution Function (CDF) of positioning errors in each case was given in Figure 9. From these figures, we confirm that the distribution of positioning error was quite good. The positioning accuracy has decreased somewhat when we consider the influence of noise. However, the increase in positioning error is in a small range. More detailed assessments are presented in the next section.

This section presented numerical simulations related to mean positioning error, minimum error, maximum error, and standard deviation when applying trilateration and ensemble learning algorithms, respectively. The obtained results are shown in Tables 3, 4, and 5. Each table corresponds to a particular layout (i.e. 3 LEDs, 4 LEDs, 5 LEDs).

In the case of 3 LEDs, the positioning results before and after considering the influence of noise are entirely different. When we neglected the effect of noise, the mean positioning error was 0.021 m, but this value increased
Figure 7. Position estimation results without noise: (a) 3 LEDs; (b) 4 LEDs; (c) 5 LEDs.

Figure 8. Position estimation results with noise: (a) 3 LEDs; (b) 4 LEDs; (c) 5 LEDs.

Figure 9. Cumulative Distribution Function of position errors: (a) 3 LEDs; (b) 4 LEDs; (c) 5 LEDs.

Table 5. Positioning errors in case of 5 LED.

| Positioning Errors       | Without noise | With noise |
|--------------------------|---------------|------------|
|                         | Trilateration | Ensemble   | Trilateration | Ensemble   |
| Maximum Error (m)        | 0.208         | 0.034      | 1.768         | 0.541      |
| Mean Error (m)           | 0.018         | 0.002      | 0.591         | 0.009      |
| Standard deviation (m)   | 0.020         | 0.012      | 0.385         | 0.047      |

significantly up to 0.793 m when the noise was applied. It proves that the trilateration algorithm is not stable under the influence of noise. An opposite result appeared when using the ensemble learning algorithm. The positioning accuracy before and after the presence of noise is quite similar, with values of 0.012 m and 0.023 m, respectively.
4. Conclusion

In this paper, we applied ensemble learning and trilateration algorithms to improve the positioning accuracy of the VLP system under the negative effect of noises. The simulation results show that the system’s performance is significantly improved after the ensemble learning algorithms are applied. Specifically, the positioning accuracy under the detrimental effect of noise is 0.023, 0.011, and 0.009 m correspond to the cases of 3, 4, and 5 LEDs, respectively. The above research results further demonstrated the feasibility of IPS in realistic environments where the LED structure often changes, and interference always exists.

Disclosure statement

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