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Performance Analysis of the Particle Swarm Optimization Algorithm in a VLC System for Localization in Hospital Environments

Diego Alonso Candia [1], Pablo Palacios Játiva [1,*], Cesar Azurdia Meza [2,*], Iván Sánchez [3,*] and Muhammad Ijaz [4]

1 School of Informatics and Telecommunications, Universidad Diego Portales, Santiago 8370067, Chile; diego.alonso1@mail.udp.cl
2 Department of Electrical Engineering, Universidad de Chile, Santiago 8370451, Chile
3 Department of Telecommunication Engineering, Universidad de Las Américas, Quito 170513, Ecuador
4 School of Engineering, Manchester Metropolitan University, Manchester M15 6BH, UK; m.ijaz@mmu.ac.uk
* Correspondence: pablo.palacios@mail.udp.cl (P.P.J.); cazurdia@ing.uchile.cl (C.A.M.); ivan.sanchez.salazar@udla.edu.ec (I.S.); Tel.: +56-93684-8919 (P.P.J.); +56-965813697 (C.A.M.); +593-9-8220-4905 (I.S.)

Abstract: Localization in hospitals can be valuable in improving different services in medical environments. In this sense, an accurate location system in this environment requires adequately enabling communication technology. However, widely adopted technologies such as Wireless Fidelity (WiFi), Bluetooth, and Radio Frequency Identification (RFID) are considered poorly suited to enable hospital localization due to their inherent drawbacks, including high implementation costs, poor signal strength, imprecise estimates, and potential interference with medical devices. The increasing expenses associated with the implementation and maintenance of these technologies, along with their limited accuracy in dynamic hospital environments, underscore the pressing need for alternative solutions. In this context, it becomes imperative to explore and present novel approaches that not only avoid these challenges but also offer more cost effective, accurate, and interference-resistant connectivity to achieve precise localization within the complex and sensitive hospital environment. In the quest to achieve adequate localization accuracy, this article strategically focuses on leveraging Visible Light Communication (VLC) as a fundamental technology to address the specific demands of hospital environments to achieve the precise localization and tracking of life-saving equipment. The proposed system leverages existing lighting infrastructure and utilizes three transmitting LEDs with different wavelengths. The Received Signal Strength (RSS) is used at the receiver, and a trilateration algorithm is employed to determine the distances between the receiver and each LED to achieve precise localization. The accuracy of the localization is further enhanced by integrating a trilateration algorithm with the sophisticated Particle Swarm Optimization (PSO) algorithm. The proposed method improves the localization accuracy, for example, at a height of 1 m, from a 11.7 cm error without PSO to 0.5 cm with the PSO algorithm. This enhanced accuracy is very important to meet the need for precise equipment location in dynamic and challenging hospital environments to meet the demand for life-saving equipment. Furthermore, the performance of the proposed localization algorithm is compared with conventional positioning methods, which denotes improvements in terms of the localization error and position estimation.

Keywords: particle swarm optimization (PSO); received signal strength (RSS); Visible Light Communication (VLC); Visible Light Positioning (VLP)

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1. Introduction

Localization systems are relevant in the current dynamics of society because they facilitate decision making, monitor critical processes, and optimize resources. In practice, one of the goals of these systems is to know the position of mobile devices, airplanes, cars, and warehouse products in indoor environments. The deployment of such systems in hospital settings marks a significant advance, offering profound benefits not just in theoretical capacity but demonstrated through practical applications. An extensive scoping review of the use of Indoor Positioning Systems (IPSs) in healthcare facilities reveals their critical role in enhancing the operational efficiency, improving patient care, and managing hospital resources with greater precision [1,2]. For front-line healthcare providers, including nurses and medical personnel, the ability to locate accurately and in real time not only themselves but also patients, medical equipment, and other essential resources translates into improved response times, a reduced workload, and a more streamlined healthcare delivery process [3].

The necessity for such localization systems in hospital environments is based on several compelling reasons. Firstly, the high-stakes nature of healthcare requires swift decision making and responses, particularly in emergencies. The ability to identify the exact location of life-saving equipment, such as defibrillators or ventilators, can significantly reduce the time to intervention [4]. Similarly, tracking the movement of patients, especially those vulnerable or with cognitive impairments, improves patient safety and prevents wandering or elopement incidents [5]. Moreover, the optimization of asset utilization through real-time tracking minimizes wasted resources and ensures that resources are readily available when needed, thereby reducing operational costs and increasing efficiency [6].

Several applications within hospital settings highlight the versatility and benefits of localization systems. These include, but are not limited to:

- **Medical devices tracking:** monitoring the location and status of medical equipment, such as portable imaging machines and defibrillators, to prevent loss and ensure availability [2,7].
- **Patient monitoring:** Offers real-time tracking of patient locations within the hospital [8–10]. This feature is especially critical in psychiatric units or for patients with conditions like Alzheimer's disease, where patient safety and the prevention of wandering are of paramount importance.
- **Staff coordination:** By providing real-time data on the locations of medical staff, hospitals can enhance their operational efficiency [11,12]. This allows for a quick assembly of teams in emergency situations and the better allocation of staff resources across the facility, directly impacting response times and patient care quality.
- **Navigation assistance:** Helps in guiding patients and visitors through the complexities of hospital layouts [13].

The gains from these applications are multiple, extending the benefits to a wide spectrum of end users, including medical personnel, patients, and hospital administrators. Among these benefits are an improved operational efficiency, which streamlines healthcare delivery; improved patient care, ensuring timely and appropriate interventions; increased safety, safeguarding patients and staff alike; and a significant reduction in asset loss and mismanagement, optimizing the use of valuable hospital resources. These tangible benefits collectively contribute to a more effective, efficient, and patient-centered healthcare ecosystem.

Given the significant advantages, the argument for integrating localization systems in hospital environments is compelling. However, the development and implementation of these systems are fraught with challenges, such as mitigating electromagnetic interference with medical equipment, achieving high precision, and managing costs effectively. Ensuring that these advanced technological systems operate in harmony with essential medical devices requires thorough testing and the application of sophisticated engineering solutions to prevent any negative impact. Furthermore, the accuracy of localization systems is critical in healthcare environments, where even slight deviations can have profound consequences on patient care outcomes. This necessitates a careful approach to system design and deployment, emphasizing reliability and precision to support the complex needs of clinical operations. In this context, the Global Positioning System (GPS) is one of the most widely used techniques to monitor devices in outdoor locations [14]. However, this system has some imprecisions in several indoor areas, such as hospitals, subways, mines, and hostile zones due to attenuation, which can be caused by obstacles. This important challenge requires new and robust forms of localization supported by efficient and stable communication systems.

In this sense, efforts to improve the accuracy of positioning systems are diverse in terms of their algorithmic approach and the communication infrastructure they use to compute a user/device's localization. Some examples of enabling technologies for these effects are Wireless Fidelity (WiFi) [15,16], Bluetooth [17,18], and Radio Frequency Identification (RFID) [19], among others [20]. Nevertheless, it is crucial to acknowledge the challenges associated with deploying these technologies in hospital settings for medical equipment tracking. Interference with medical devices [21], inaccuracies in the results obtained, and high implementation costs have been observed [22]. To mitigate these drawbacks, Visible Light Communication (VLC)-based systems have emerged in the past decade as a viable communication alternative to enable localization in indoor environments.

To validate and verify the use of VLC systems in these hospital environments, recent studies have introduced a hybrid wireless tracking system that integrates technologies such as VLC, Visible Light Positioning (VLP), and power line communication (PLC) for smart hospital operations [23,24]. These research and implementation works use VLC for downlink communication, while infrared (IR) was used for uplink communication. Furthermore, in the literature, there are few works related to VLC applied to the localization of medical equipment in hospitals [25,26]. On the other hand, in [27], the authors focus mainly on simultaneous positioning and orientation using VLC. In contrast, our work specifically addresses the localization of medical equipment in hospital environments through VLC. Although Zhou et al. explore positioning and orientation in a broader context, our approach uniquely utilizes three LEDs with different wavelengths, emphasizing the integration with existing hospital lighting infrastructure, and proposes a comprehensive comparison with conventional trilateration methods. Furthermore, our work considers future improvements, such as the incorporation of optical filters, to improve precision in healthcare settings. In [28], the authors present an Indoor Positioning System that uses VLC and PSO for improved precision. On the contrary, our work distinguishes itself by proposing a medical equipment localization system within hospital environments by using VLC. Although Cai et al. emphasize high precision in a broader indoor context, our method specifically tailors the technology to address the challenges of healthcare settings by introducing three LEDs with different wavelengths, emphasizing integration with existing lighting infrastructure, and planning a detailed comparison with conventional trilateration methods. Furthermore, our work contemplates future advances, including the incorporation of optical filters for a comprehensive assessment. Despite efforts by the specialized community to propose VLC-based systems to improve localization applications in hospital environments, to the authors' knowledge, localization accuracy can still be improved. We believe that this improvement can be achieved with the implementation of tools widely used today, such as artificial intelligence algorithms or machine learning.

On the basis of this premise, the objective of this work is to present a medical equipment localization system within the hospital environment. The proposed system uses three LEDs as transmitters with different wavelengths as a modification of Color Shift Keying (CSK) modulation, which allows one to form a trilateration with the position of the target to be located. Taking into account the intrinsic characteristics of light, an efficient localization mechanism can be obtained, which is improved by introducing a Particle Swarm Optimization (PSO) algorithm. This algorithm along with the complete VLC system is validated through simulations that involve positioning using the proposed PSO algorithm. Initially, the simulations do not include the use of specific optical filters for the application, but future work will incorporate this feature to enable a comprehensive comparison.

It is important to note that this methodology is highly applicable in hospital environments due to its strategic use of VLC and existing lighting infrastructure. Some important technical reasons are described below to justify this statement:

- **Utilization of LEDs with different wavelengths:** The implementation of three transmitting LEDs with different wavelengths serves a crucial purpose. First, it enables multiplexing, allowing simultaneous data transmission using different light frequencies. This feature significantly improves the system's capacity, accommodating more information transmission channels. In addition, different wavelengths provide diversity, reducing the likelihood of interference and enhancing the reliability of communication in complex hospital settings with various electronic devices [29].
- **CSK modified modulation:** The implementation of three transmitting LEDs with different wavelengths serves a crucial purpose. First, it enables multiplexing, allowing for simultaneous data transmission using different light frequencies. This feature significantly improves the system's capacity, accommodating more information transmission channels. In addition, different wavelengths provide diversity, reducing the likelihood of interference and enhancing the reliability of communication in complex hospital settings with various electronic devices [29].
- **Employment of Received Signal Strength (RSS) method:** The RSS methodology is preferred for its ability to precisely measure signal strength, which correlates directly with the distance between the transmitter and receiver. This method offers a more accurate and stable distance estimation compared to other techniques, such as Time of Flight (ToF) or Angle of Arrival (AoA), which can be susceptible to environmental interference and multipath effects. In a hospital environment, where precision is paramount, the robustness and reliability of RSS make it a superior choice.
- **Integration of the PSO scheme in trilateration:** The incorporation of the Particle Swarm Optimization (PSO) scheme within the trilateration algorithm improves the efficiency of the method in determining the precise location of equipment or instruments. PSO is particularly adept at optimizing complex, non-linear functions, making it well suited for refining the calculation of coordinates in a three-dimensional space. This adaptability and optimization capability contribute to minimizing localization errors, which is critical in healthcare settings where accuracy is non-negotiable [30].
- **Advantages over other methods:** Compared to traditional technologies such as WiFi, Bluetooth, and RFID, the proposed method excels in addressing the unique challenges posed by hospital environments. The use of VLC mitigates interference with medical devices, while the RSS method and PSO scheme collectively outperform alternative proximity estimation and optimization techniques. The integration of these elements results in a comprehensive solution that offers superior accuracy, reduced costs, and improved compatibility within the complex and sensitive hospital setting [31,32].

The proposed method stands out from existing solutions through its strategic integration of VLC using three LEDs with different wavelengths, coupled with a PSO-enhanced trilateration algorithm. Unlike conventional technologies, such as WiFi, Bluetooth, or RFID, the system takes advantage of the inherent lighting infrastructure in hospitals, minimizing deployment costs and possible interference with medical devices. The use of different wavelengths facilitates multiplexing and reduces interference, addressing the challenges faced by single-wavelength solutions. Furthermore, the precision of localization is refined through the RSS method. These collective features offer a comprehensive solution tailored to the complex needs of hospital environments, surpassing existing methods in precision, cost-effectiveness, and compatibility. In the following, we detail each of the advantages of these system components in Table 1.

Table 1. System components and advantages.

Component	Advantages	Explanation
Multiwavelength LEDs [29]		
	Enhanced precision	Using LEDs with different wavelengths allows for improved precision in distance estimation. Different wavelengths allow the system to account for variations in the environment, such as potential obstructions or reflections, providing a more accurate representation of the actual distance between the transmitter and the receiver.
	Mitigation of interference	The use of multiple wavelengths reduces the likelihood of interference with other light sources or electronic equipment in the hospital. This is especially crucial in healthcare settings, where the coexistence of various technologies is common.
RSS Method [30]		
	Accuracy in dynamic environments	The RSS method excels in providing accurate distance estimates even in complex and dynamic hospital environments. Its reliance on signal strength allows for real-time adjustments, accommodating changes in the surroundings or potential obstacles, which is particularly vital in areas where equipment or the movement of medical personnel is frequent.
	Reduced environmental interference	Unlike some other methods that can be affected by environmental noise, the RSS method is less susceptible to interference, contributing to a more reliable and stable localization process.
PSO Scheme [33]		
	Optimized trilateration	Integrating the PSO scheme into the trilateration algorithm optimizes the localization process. PSO enhances the convergence speed of the algorithm, ensuring a faster and more accurate determination of the target location. This is especially advantageous in time-sensitive medical scenarios.
	Robustness to non-line-of-sight (NLOS) Situations	PSO aids in overcoming the challenges posed by NLOS scenarios, common in indoor environments. It allows the algorithm to adapt and converge even when the direct line-of-sight (LOS) is obstructed, contributing to the overall robustness of the system.

Compared to traditional methods like WiFi, Bluetooth, or RFID, which may struggle with accuracy, interference, and dynamic environmental changes, the proposed combination of multiwavelength LEDs, RSS, and PSO stands out as a more sophisticated and adaptive solution, tailored to meet the stringent demands of precise localization within the sensitive and ever-changing hospital environment.

In this sense, the main contributions provided by this work can be summarized as follows:

- To propose a system based on Color Shift CSK modified modulation for localization, utilizing three transmitting LEDs with different wavelengths, enabling differentiation without transmitting any information.
- To implement a trilateration algorithm incorporating the PSO algorithm for precise localization.
- To compare the proposed positioning algorithm with several conventional trilateration and localization methods used in other research.

Regarding the organization of the article, the following details are provided. Section 2 describes the implemented VLC system along with its main features. Section 3 describes the PSO algorithm implemented for trilateration. Section 4 provides a detailed description of the procedure, presents the parameters used in the simulation of the system, and discusses the results obtained. Finally, Section 5 concludes the article by summarizing the key findings and drawing conclusions from the work carried out.

2. VLC System Model

To give an overview of the most important parts of the system, we divided this section into transmitter, CSK modulation, receiver, and VLC channel, along with the methodology, to obtain the distance between the transmitter and receiver.

2.1. Transmitter

The objective of the proposed solution is to take advantage of the lighting infrastructure in hospitals. Therefore, the proposed solution uses three optical transmitters, each of which consists of a single LED. These light sources emit different wavelengths that are suitable for the hospital environment. These wavelengths must have enough separation between them so that the optical receiver can distinguish between the different LEDs. This difference between wavelengths provides an advantage for transmitter identification. Therefore, there is no need to transmit the identification of the LED as data. However, it is necessary to keep the LEDs continuously emitting light at a constant power. Using various wavelengths in the transmitters offers a significant benefit as it eliminates the need for data transmission to identify each LED. This means that the hardware required for light modulation is not necessary, simplifying the system's design and reducing its complexity.

It is important to mention that, for the localization of the receivers, it is essential to know the positions of the transmitters in the scenario. Figure 1 illustrates the localization system, where each LED emits light that is received by a specific Photo-Diode (PD) in the optical reception stage. For practical purposes, it is assumed that the three LEDs are oriented in a vertical direction, pointing toward the floor of the room.

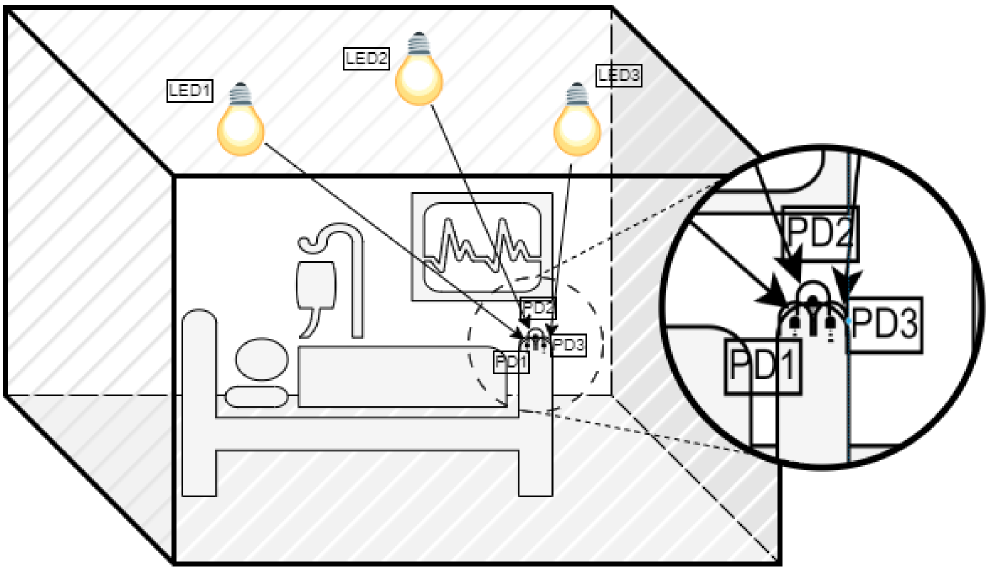

Figure 1. General outline of the proposed localization system.

In terms of the wavelength features to be used, the allocation mechanism adopted by the CSK modulation is implemented, which will be explained below.

2.2. Color Shift Keying Modulation

As we mentioned above, it is necessary to assign a transmission wavelength to each of the three transmitters. This assignment must meet the following two criteria:

- Optical transmitters must emit light at wavelengths suitable for the hospital environment.
- Optical transmitters must emit light at wavelengths sufficiently separated from each other.

Although no data are transmitted through the optical medium, according to the aforementioned premises, the modulation scheme based on CSK specified in PHY III of the IEEE 802.15.7 standard [34] is adopted and modified. This mechanism is designed to provide high data rates in indoor environments and uses the Commission Internationale de l'Éclairage (CIE) 1931 xy color diagram. This standard is exemplified by three RGB LEDs. However, given the hospital environment, it is not possible to use RGB LEDs. While the CIE color diagram is primarily focused on specifying colors, the concept of illuminants can be considered in the context of white light. To achieve the desired goal, represented by the coordinate (x_c, y_c) within the CIE 1931 system, a careful selection of three LEDs is made. These LEDs are chosen to emit light with coordinates that closely align with (x_c, y_c), forming a triangle within the diagram. When controlling the intensity of these light sources, different variations of white light can be achieved within the geometric shape defined by the coordinates of the three LEDs. This approach ensures that significant color differences are minimized, allowing the system to maintain a consistent and harmonious lighting output suitable for the hospital environment.

To set the position of the LEDs, we consider (x_i, y_i) as the coordinates of each of the three LEDs within the CIE 1931 xy system, where $i \in \{1, 2, 3\}$. These coordinates form a triangle within the diagram. Let us assume that (x_c, y_c) lies within this triangle. Based on the intensity I_i of each LED, it is possible to generate the color described at this point. In other words, the intensity I_i is associated with the transformation of the coordinate (x_i, y_i). The relationship between these coordinates and the intensities is specified in the mentioned standard as [34]

$$x_c = \sum_{i=1}^{3} x_i * I_i, \tag{1}$$

$$y_c = \sum_{i=1}^{3} y_i * I_i, \tag{2}$$

$$\sum_{i=1}^{3} I_i = 1. \tag{3}$$

In this context, the optical receiver must be able to differentiate between the three transmitters on the basis of the wavelength emitted by each of them.

2.3. Receptor

To differentiate the sources (transmitters) of light beams entering the receiver, it is made up of three PDs, each of them equipped with a wavelength light beam filter corresponding to the wavelengths used by the transmitters. This dynamic is illustrated in Figure 2. It should be noted that for illustrative purposes, in Figure 2, the colors are used only to distinguish the light that a PD receives about a specific LED. Here, ψ_i represents the angle of light irradiation by the LED with respect to the location of the PD, ϕ_i denotes the angle of incidence of light on the PD, and d_i corresponds to the Euclidean distance between the PD and the LED i at position (x_i, y_i, z_i). For simplicity, it should be noted that the three PDs used are treated as if they were located together.

In the context of the orientation of LEDs and PDs, it is assumed that the receiver PDs are oriented vertically upward. In addition, it is assumed that the transmitters are aligned in the same direction and pointing downward. Under this assumption, it can be inferred that $\phi_i = \psi_i$.

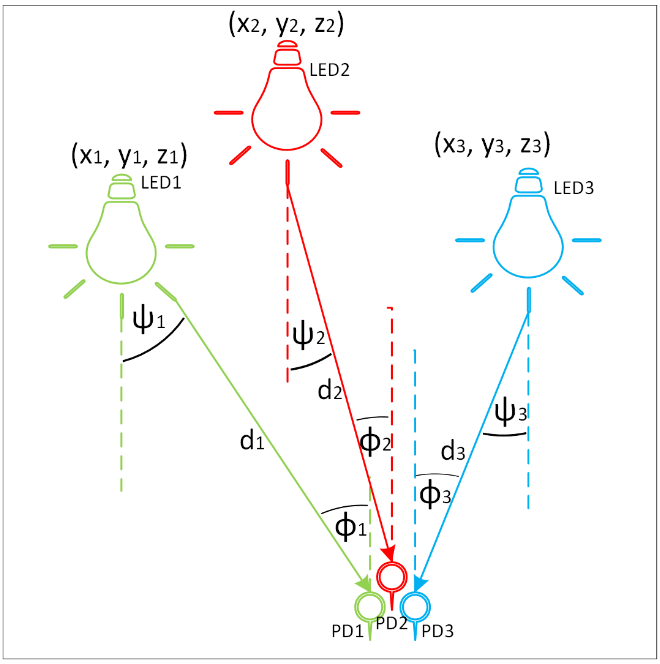

Figure 2. Transmission and reception dynamics.

Furthermore, it is necessary to take into account the gain of the optical concentrator, which is represented by [35]

$$g_i(\psi_i) = \begin{cases} \frac{n_i^2}{\sin^2 \Psi_{c_i}}, & 0 \leq \psi_i \leq \Psi_{ci} \\ 0, & \psi_i > \Psi_{ci}, \end{cases} \quad (4)$$

where n_i represents the refractive index of the optical concentrator and $\Psi_{ci} < \pi/2$ denotes the Field of View (FoV) of the PD. It is also important to include and consider the impact of the optical filter gain ($T_s(\psi_i)$) on signal reception.

Continuing with the process of receiving and processing the optical signal received, the power received from each PD is measured and transmitted to a processing system via WiFi by using the IEEE 802.11 standard [36]. This process is carried out to determine the distance between the receiver and each LED, enabling an estimation of the target's location. In addition, the use of WiFi as an uplink provides the advantage of using existing infrastructure within the hospital. The decision to use Wi-Fi only as a communication technology for uplink without adopting existing Wi-Fi-based localization algorithms is the result of the nuanced requirements of hospital equipment localization and certain technical reasons that are detailed below:

- **Accuracy and precision:** WiFi-based location algorithms may not offer the same level of precision and precision needed to locate hospital equipment. VLC-based schemes, which use three LEDs with different wavelengths and incorporate a trilateration algorithm enhanced by PSO, are designed specifically to address the stringent accuracy demands of medical equipment localization [37].
- **Interferences and environmental factors:** Hospital environments can be dynamic and subject to various interferences. WiFi signals can be affected by environmental factors, causing fluctuations in accuracy. VLC, which operates in the visible light spectrum, is less prone to interference and provides a more stable and reliable means of localization [38].
- **Customization for hospital requirements:** The proposed method is designed taking into account the unique characteristics of hospital environments. The choice of VLC

and the specific modifications made, such as the use of different wavelengths for LEDs, are designed to overcome the specific challenges of healthcare settings.

In the described localization system, the receivers are also equipped with WiFi modules/interfaces, allowing wireless data transmission over the existing WiFi infrastructure of the hospital, a standard feature in modern healthcare facilities [39,40]. This design leverages the hospital-wide WiFi network to ensure the efficient delivery of location information from optical receivers to the Central Processing Unit (CPU). The CPU, equipped with the PSO algorithm, processes the received data to determine the approximate location of the receiver and, consequently, the object or equipment to be located. Utilizing the existing WiFi infrastructure for data transmission eliminates the need for additional physical connections or proprietary networks, facilitating seamless data transfer and enabling real-time processing and analysis.

Considering the technical factors widely discussed in the literature, we assume that in optical receivers, in addition to the PD, there are optical filters with a bandwidth of 20 nm and central wavelengths of 520, 540, and 560 nm. This selection ensures an adequate distinction between the wavelengths emitted by each LED, thus minimizing significant overlap and interference between different LED signals. As a result, the optical receiver can differentiate and identify each transmitter based on the received wavelength. Moreover, the selected parameters are practically compatible with existing LED technology and readily available filters, making the implementation of the proposed system highly feasible.

2.4. VLC Channel

As explained in previous sections, although in this work, the mechanism implemented by CSK modulation is not used directly for data communication, its use takes advantage of the properties of light and its propagation. Thus, the methodology employed uses the power received to locate the target. To achieve this goal, various factors that affect the VLC channel must be considered. Consequently, the power received at the target can be accurately described as [41]

$$P_{Ri} = P_{LOSi} + P_{Noise}, \tag{5}$$

where P_{Ri} represents the power received from LED i, P_{LOSi} denotes the power corresponding to the LOS component, and P_{Noise} represents the noise power. This study exclusively takes into account thermal and shot noise [42,43]. Additionally, in this study, it is assumed that the system does not consider interferences from other luminaires. Furthermore, P_{LOS} can be expressed as

$$P_{LOSi} = H_{LOSi}(0)P_{ti}, \tag{6}$$

where H_{LOSi} represents the channel gain for the LOS component and P_{ti} denotes the transmitted power. H_{LOSi} can be mathematically described as [35]

$$H_{LOSi}(0) = \begin{cases} \frac{A_{ri}(m_i+1)}{2\pi d_i^2} \cos^{m_i}(\phi_i)\cos(\psi_i)T_s(\psi_i)g(\psi_i), & 0 \le \psi_i \le \Psi_{ci} \\ 0, & \psi_i > \Psi_{ci}, \end{cases} \tag{7}$$

where A_{ri} denotes the area over which the PD i receives light and m_i represents the Lambertian order defined as

$$m_i = \frac{-\ln 2}{\ln(\cos \phi_{1/2,i})}, \tag{8}$$

where $\phi_{1/2,i}$ represents the semi-angle at half the illuminance of an LED i. It has previously been established that $\phi_i = \psi_i$. Then, the application of Equations (6) and (7) results in the following expression:

$$P_{LOSi} = \frac{A_{ri}(m_i+1)}{2\pi d_i^2} \cos^{m_i+1}(\phi_i)T_{si}(\psi_i)g_i(\psi_i)P_{ti}. \tag{9}$$

2.5. Distance between the Receiver and the LEDs

The aim is to obtain the distance between the LED i and the medical device. To achieve this goal, it is essential to note that the position of each LED is known. Let (x_t, y_t, z_t) be the location of the medical device that is currently unknown. Thus, the distance from LED i to the receiver can be expressed as

$$d_i = \sqrt{(x_i - x_t)^2 + (y_i - y_t)^2 + (z_i - z_t)^2}. \tag{10}$$

Moreover, considering the right triangle formed by the distance from the height of the receiver to the position of the LEDs on the ceiling of the chamber, the relationship can be expressed as

$$\cos(\phi_i) = \frac{z_i - z_t}{d_i}. \tag{11}$$

The target position must necessarily include all three dimensions. However, achieving accurate three-dimensional (3D) localization poses challenges in terms of algorithm complexity or reduced precision [44]. To simplify the calculations, it is assumed that the receiver in the device is positioned at a known height h relative to the floor of the room. By combining Equations (9) and (11), the following expression is obtained:

$$P_{LOSi} = \frac{A_{ri}(m_i + 1)}{2\pi} T_{si}(\psi_i) g_i(\psi_i) P_{ti} * \frac{(z_i - z_t)^{m_i+1}}{d_i^{m_i+3}}. \tag{12}$$

Rearranging Equation (12), we obtain the following expression:

$$d_i = \left(\frac{A_{ri}(m_i + 1)}{2\pi} T_{si}(\psi_i) g_i(\psi_i) P_{ti} \frac{(z_i - z_t)^{m_i+1}}{P_{LOSi}}\right)^{\frac{1}{m_i+3}}. \tag{13}$$

It is observed that the equation depends solely on the received power at PD i.

3. Trilateration and PSO Algorithms

Once the estimated distances from the receiver to each LED are obtained, the localization of the target can be formulated as an optimization problem [45]. The pseudocode of the PSO is shown in Algorithm 1. The mathematical expression proposed for this problem is expressed by

$$\sum_{i=1}^{3} (d_{pi} - d_i)^2, \tag{14}$$

where d_{pi} represents the distance from a test point $P(x, y, h)$ to LED i. This point varies in the search for a value of d_{pi} that minimizes Equation (14). To obtain an optimized solution, the utilization of a PSO algorithm is proposed. The steps to follow can be divided into two parts.

3.1. Obtaining an Initial Solution

To obtain an initial solution, the X-axis is discretized into k equidistant points and the Y-axis is divided into t equidistant points for each segment. This approach initially results in a total of $k \times t$ points. The point POS_p with coordinates (x_p, y_p, h) represents the initial position of the particle p.

After obtaining the initial particles, the objective function is computed for each of them. Subsequently, the initial velocity of each particle is defined by using a uniformly distributed random number within the range $[0, 1]$. Furthermore, the position and value of the objective function where the best value is achieved among all particles are stored as $gbest$. Lastly, for each particle, the best position and the corresponding value of the objective function achieved by that particle are recorded as $pbest_p$.

Algorithm 1 Particle Swarm Optimization algorithm

Particle initialization by dividing the XY plane
for iteration **do**
  for all particle **do**
    Update velocity
    Update position
    Evaluate the objective function value of the particle
    if Particle objective function value $< pbest$ **then**
      Update *pbest*
    end if
    if Particle objective function value $< gbest$ **then**
      Update *gbest*
    end if
  end for
end for

3.2. Iterations

Once the particles are obtained, the iteration of the PSO algorithm proceeds. First, the velocity of each particle in iteration t, denoted by v_t, is updated by using the following expression [46]:

$$v_{t+1} = w \times v_t + r_1 \times c_1 \times (pbest_p - POS_p) + r_2 \times c_2 \times (gbest - POS_p). \tag{15}$$

Equation (15) incorporates the inertia weight w; random numbers r_1 and r_2 uniformly distributed within the range $[0, 1]$; and acceleration coefficients c_1 and c_2, which determine the importance given to the particle's personal best ($pbest_p$) and the global best ($gbest$), respectively. Parameters c_1 and c_2 are commonly referred to as the cognition of the particle and the social influence of the swarm, in the given order [46].

Next, the algorithm updates the position of particle p for the next iteration based on

$$POS_{t+1} = POS_t + v_{t+1}. \tag{16}$$

Finally, the objective function value of each particle is updated based on Equation (14). Consequently, each particle updates the parameters $gbest$ and $pbest_p$ if they are found to be smaller than the current values.

One conventional method of obtaining an estimated receiver position is by solving equation [44,45]:

$$\begin{bmatrix} x_2 - x_1 & y_2 - y_1 \\ x_3 - x_1 & y_3 - y_1 \end{bmatrix} \begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} (R_1^2 - R_2^2) + (x_2^2 + x_2^2) - (x_1^2 + y_1^2) \\ (R_1^2 - R_3^2) + (x_3^2 + x_3^2) - (x_1^2 + y_1^2) \end{bmatrix}, \tag{17}$$

where R_i is the result obtained from Equation (13) and can be expressed as

$$\begin{aligned} R_i^2 &= (x_i - x_t)^2 + (y_i - y_t)^2 \\ &= \left(\frac{A_{ri}(m_i + 1)}{2\pi} T_{si}(\psi_i) g_i(\psi_i) P_{ti} \frac{(z_i - z_t)^{m_i+1}}{P_{LOSi}} \right)^{\frac{2}{m_i+3}} - (z_i - z_t)^2. \end{aligned} \tag{18}$$

Equation (17) arises from working with the distance equation from the receiver to each LED, which is shown in expression (13).

4. Simulation, Results, and Discussion

To evaluate the performance of the VLC system in conjunction with the PSO-enhanced localization mechanism, an indoor hospital scenario was simulated by using computer software

(Python 3.7.0). This environment is built based on the graphical sketch shown in Figure 1. The object to be placed in the hospital room, which could be considered a stretcher, for example, is located in the indoor environment that measures (5 × 5 × 3) m. Within this hospital room, there are three LEDs at known positions, where LED_1 is located at the coordinates (1, 2, 3) m, LED_2 at (1, 4, 3) m, and LED_3 at (4, 3, 3) m. The receiver is positioned above the target, as depicted in Figure 1, and consists of three PDs that point directly to the ceiling, following the suggestion in Equation (12) where $\phi_i = \psi_i$. Moreover, these are considered as if they were in the same location within the space. It is important to note that each PD receives power from a single LED.

On the other hand, the selection of the PSO parameters was performed through an iterative process that involved the extensive testing of the algorithm and its performance. This involves evaluating various parameter settings to identify the one that produces the best results. This methodological approach involves systematic experimentation with different combinations of parameter values to optimize the behavior of the algorithm based on specific performance metrics and to select the configuration that demonstrates the highest degree of effectiveness according to the predefined criteria to be evaluated [47,48].

To verify the system, a height is defined for the receiver and the XY plane is divided into 10 × 10 points. This implies dividing the 5 m length of the room into 10 points that are spaced 50 cm apart. The same division is then performed for the width of the room in each of these divisions. This means that 100 points are tested for one specific height. The decision to divide the space into 100 points, each of which positions a particle, is based on the balance between spatial resolution and computational complexity. This methodology allows for uniform coverage of the area of interest while maintaining a manageable number of particles.

The evaluation of these points is repeated for the four localization methods to be compared: solving Equation (17), which is the conventional method, by using the proposed PSO algorithm, without the PSO algorithm, and a localization algorithm with VLC-enabling technology based on multilevel modulation [49]. Then, this process is repeated by varying the height between 0 and 2.5 m with an increment of 0.1 m for each test.

To assess the performance of the localization algorithms used, the error is measured as the distance between the estimated and actual positions. This is expressed as follows:

$$d_{error} = \sqrt{(x_t - x_r)^2 + (y_t - y_r)^2}. \tag{19}$$

Finally, the technical parameters used for the simulation of the hospital scenario, the VLC channel, and the PSO algorithm are shown in Table 2 [42,43].

4.1. PSO Algorithm Performance Analysis

The initial phase of this study involves understanding how the division of space for particle initialization in the PSO algorithm affects its accuracy. This is explored by testing the algorithm with various swarm sizes, the results of which are depicted in Figure 3. The image showcases four distinct curves, each corresponding to the error with a different number of particles in the swarm: 9, 25, 100, and 400. The outcomes from these tests reveal a direct relation between the swarm size and the algorithm's accuracy: larger swarms yield more precise results. However, this increased precision comes at the cost of higher computational demand. For instance, the processing time for positioning with a small swarm of 9 particles is relatively quick at 19 ms, but this time jumps significantly to 54 ms with 100 particles and further escalates to 96 ms with a 400-particle swarm. Given these findings, a balance is struck by opting for a 100-particle swarm. This choice offers a compromise between achieving a desirable level of precision and maintaining manageable computational requirements during the testing phase.

Table 2. Positioning system parameters.

VLP System Features	**Values**
VLC Simulation Parameters	
Dimensions of the room ($w \times l \times h$) (m)	($5 \times 5 \times 3$)
Coordinates of the $LEDs$ (x_i, y_i, z_i) (m)	$LED_1 = (1,2,3)$ m, $LED_2 = (1,4,3)$ m, $LED_3 = (4,3,3)$ m,
Power of each LED_i (W)	8
Gain of each optical filter, $g_i(\psi_i)$	Unity Gain
Effective area of each PD_i, A_{ri} (m^2)	10^{-4}
Gain of each optical concentrator, g_i	Unity Gain
Photoelectric conversion efficiency ($\frac{A}{W}$)	0.54
FoV of each PD_i, Ψ_i (°)	90°
Lambertian order, m_i	1
Equivalent noise bandwidth (MHz)	100
PSO Parameters	
Initial particle velocity, v_t	$\mathcal{U}$[0,1]
Cognitive factor, c_1	1
Social factor, c_2	2
Cognitive random parameter, r_1	$\mathcal{U}$[0,1]
Social random parameter, r_2	$\mathcal{U}$[0,1]
Iterations	500
Particles	100 (space division of 10×10)
Inertia weight, w	0.8

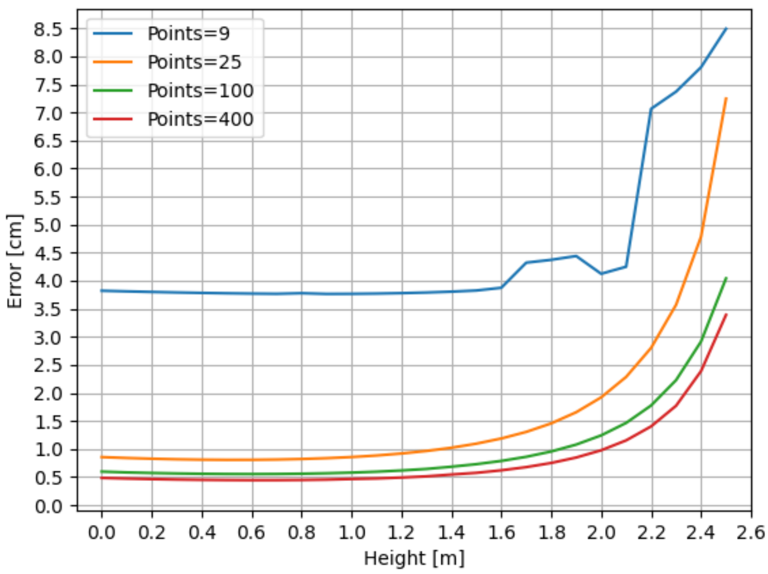

Figure 3. Localization error [cm] vs. the height of the receiver [m] for various numbers of particles.

4.2. Comparative Analysis of Localization Accuracy

Observing the results in Figure 4, it is evident that the use of the PSO method yields improvements compared to the other algorithms. Although the worst average error obtained by this algorithm is 3.96 cm at 2.5 m, the conventional method of solving the equation presented in Equation (17) results in an average error of 13 cm at the same height. Similarly, the method without the PSO algorithm yields an average error of 11.48 cm. On the other hand, the best average value for the PSO algorithm occurs at 0 m with a mean error of 0.59 cm, which is approximately half the best average achieved by the equation-solving method.

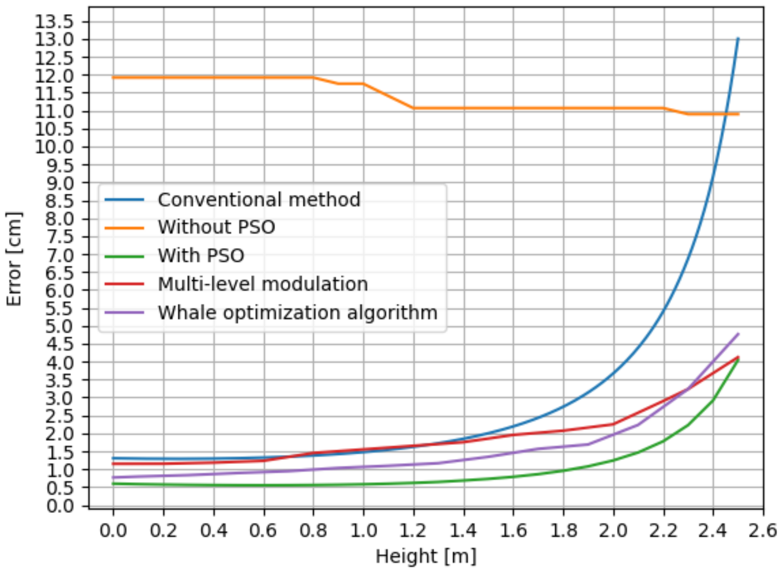

Figure 4. Localization error [cm] vs. the height of the receiver [m].

An additional observation deduced from Figure 4 is that with increasing height, there is a corresponding increase in the average error. This can be attributed to the vertical orientation of the receiver's PDs toward the ceiling, whereas the LEDs are directed toward the floor of the room. Consequently, according to Equation (11), when only the height of a point increases, the value of $\cos(\phi_i)$ decreases due to the decreasing discrepancy in $z_i - z_t$. As a result, the received power from the LOS channel decreases, leading to a reduction in the Signal-to-Noise Ratio (SNR).

Moreover, for comparative and evaluative purposes, Figure 4 also represents the curve obtained by evaluating the proposed scenario of the localization method discussed in [49]. The system employs a novel algorithm that uses the difference in received voltage levels with multilevel modulation to minimize the noise impact. This approach is combined with the minimum mean squares error algorithm and an extended Kalman filter. Consequently, according to the results, the PSO algorithm exhibits greater precision in receiver positioning. The accuracy of the localization system employing multilevel modulation is comparable to the conventional method for heights under 1.5 m. However, the technique presented in [49] demonstrates a lower susceptibility to error caused by height. In other words, it is less affected by receiving less power, or the LOS channel, or, equivalently, it is less sensitive to the SNR.

Another method added to the comparative analysis is detailed in [50], which involves the use of the Improved Whale Optimization Algorithm (IWOA) to improve the accuracy of the indoor localization system based on VLC [50]. The IWOA incorporates elite opposition-based learning and Lévy flights, innovative strategies designed to mitigate the influence of PD rotation, a factor that can induce substantial positioning errors. As evidenced by the research examined, the IWOA significantly reduces the average positioning error to 2.14 cm in the absence of PD rotation. However, it should be noted that the PSO algorithm presented in this study exhibits improved precision in finding a target. Compared to previous findings, it is clear that while the IWOA presents a robust approach, particularly in mitigating the challenges posed by PD rotation, the PSO algorithm excels by potentially offering greater accuracy across a range of heights, as reflected in the provided graph. This graph illustrates that the PSO maintains a relatively stable error rate regardless of height alterations, contrasting with the IWOA, which, although competitive at lower heights, exhibits a sharp increase in error beyond the 2 m mark. This comparison underscores the importance of algorithm selection based on the specific requirements of the localization task at hand.

These results demonstrate the effectiveness of the PSO algorithm in achieving more accurate localization compared to other methods. The lower average error obtained with the PSO algorithm indicates its superior performance in estimating the position of the target object. In the simulation carried out, the average execution time of the PSO algorithm was 54 ms. In comparison, the conventional method that solves Equation (17) showed an average duration of 0.033 ms, while the non-PSO approach took 0.43 ms on average, and the multilevel modulation method presents an average duration of 42 ms. Therefore, it can be observed that the trade-off for improved localization accuracy is the increased computational overhead associated with employing the PSO algorithm in this particular scenario.

Furthermore, Figure 5 shows the real and estimated positions when the receiver was placed at a height of 1.5 m above the floor. In this simulation, 76.85% of the estimates achieved an error of less than 1 cm, while 91.73% of the estimates demonstrated an error below 2 cm. These findings substantiate the algorithm's ability to deliver precise estimations with regard to the target's location. However, as expected, positions close to the corners exhibited higher estimation errors. In particular, the largest error at this height occurred at position (5.0, 3.0) m, measuring 3.48 cm.

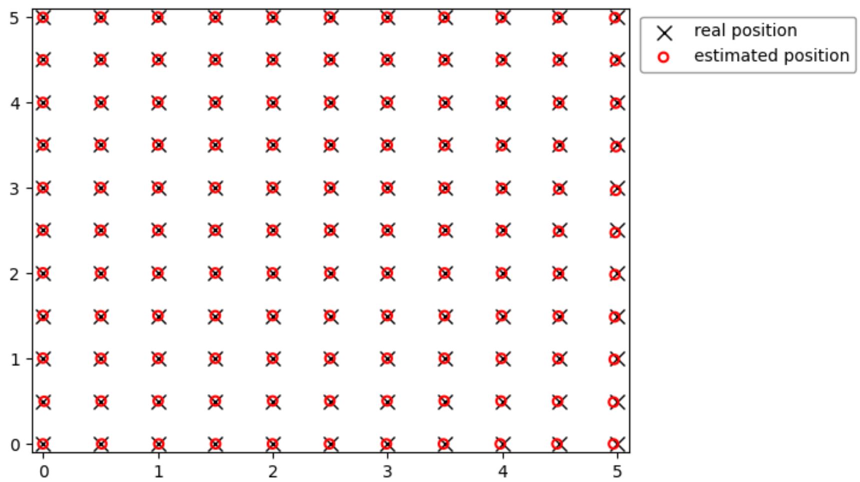

Figure 5. Real and estimated positions with the receiver at 1.5 m.

4.3. Enhancing PSO Accuracy via Particle Initialization

A critical aspect of the performance of the PSO algorithm within the proposed VLC system for localization is the strategy employed for particle initialization. Traditionally, particles are distributed randomly within the search space. However, this approach can lead to premature convergence to local optima because of the potential clustering of particles in suboptimal regions. To mitigate this problem, the proposed system incorporates a space partitioning method for particle initialization, which systematically segments the search space and ensures a more evenly distributed initialization of particles.

This novel strategy was compared to the conventional random initialization technique. As depicted in Figure 6, the partition initialization method consistently resulted in lower localization errors across a spectrum of receiver heights. This suggests a more thorough exploration of the search space and indicates a higher probability of escaping local optima, thereby enhancing the likelihood of converging to the global optimum.

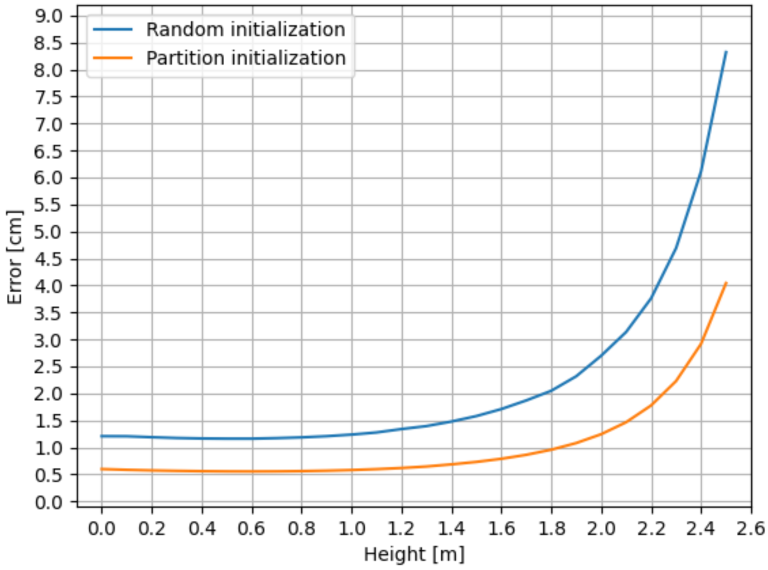

Figure 6. Localization error [cm] vs. the height of the receiver [m].

The efficacy of the partition initialization method is further underscored by the Cumulative Distribution Function (CDF) depicted in Figure 7. This graph is based on the results obtained for Figure 6, where the localization of a target is performed at various heights. The steeper ascent of the CDF curve for the partition method indicates a higher concentration of localization estimates with smaller errors. Remarkably, this method achieved a faster convergence rate, since a significant proportion of the localization tasks were completed with minimal errors, demonstrating its robustness to achieve precise localizations.

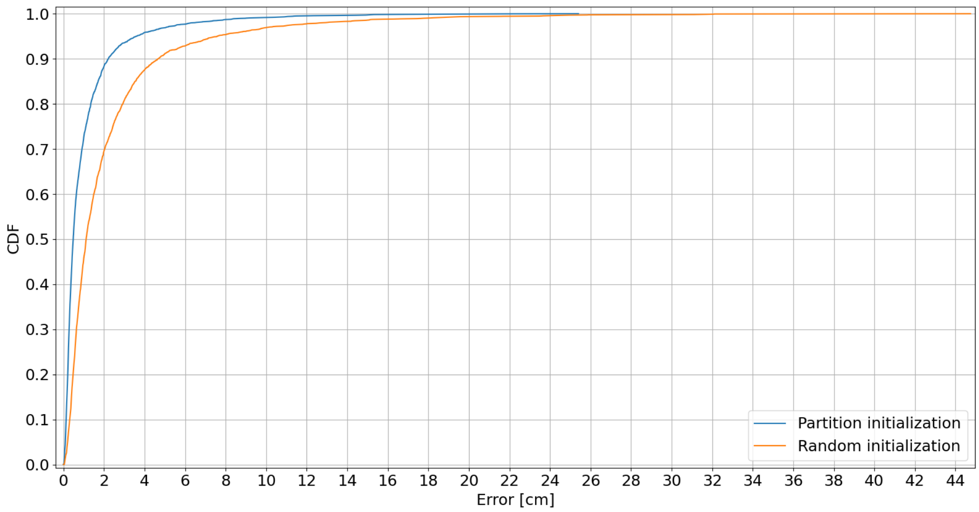

Figure 7. CDF vs. error [cm].

These findings underscore the importance of the initialization phase in the performance of the PSO algorithm for the intended VLC-based localization system. The systematic distribution of particles across the search space not only provided better accuracy but also demonstrated a consistent performance advantage over the random initialization method, as evidenced by the empirical data.

The implications of these results are profound, suggesting that the initialization process plays a crucial role in the algorithm's ability to navigate complex search spaces effectively.

This advancement in particle swarm initialization presents a promising avenue for future research and application, particularly in the critical context of hospital environments where precise localization is paramount.

5. Conclusions and Future Work

This manuscript proposes a VLC-based medical equipment positioning system that uses existing lighting infrastructure in a hospital setting. The findings demonstrate a better performance of the PSO algorithm compared to other localization methods used in VLC-based positioning systems, as evidenced by its consistently lower average errors. However, it should be noted that the increased accuracy achieved by the PSO algorithm comes at the expense of a higher computational overhead. Therefore, in practical applications, a careful trade-off between accuracy and computational efficiency must be considered.

Potential areas for future investigation include improving the computational efficiency of the PSO algorithm without compromising its precision for real-time positioning. Furthermore, it is necessary to propose and validate improvements to the PSO algorithm to adapt it to 3D environments. In this forthcoming method, the optimization of the parameters of the PSO algorithm will be studied, such as cognitive factors, inertia, number of particles, and iterations, looking for relationships between the precision of the results and the different configurations. Moreover, it is crucial to assess possibilities for investigating various setups to enhance the distribution and the number of particles used to initialize the algorithm in the examined scenario. Furthermore, future work should encompass a comparison between the advantages of this system, which employs white lights with different wavelengths, and proposals that utilize only a single wavelength. This analysis will include the evaluation of the computational performance, accuracy, computational complexity, costs, and necessary equipment. Finally, future work will include an analysis of the optical filters required for the system, which is a crucial element to carry out adequate experimental validation and analysis of the proposed system.

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