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HueLoc: Localization Through LEDs' Hue Spectrum

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***Abstract*—Over the past decade, visible light positioning has become increasingly important for precise localization systems, yet its widespread adoption is limited due to the necessity of modifying existing lighting systems. This article presents HueLoc, a novel method that bypasses this issue by using inherent features of light, such as the dominant colors in white light-emitting diode (LED) lights, and employs affordable, energy-efficient hue sensors for location services. We propose that by extracting the power at dominant wavelengths of LEDs, these can be uniquely identified using a specifically designed signature. The unique signatures can be used by mobile objects for spatial awareness and further localization using the proposed regression-based learning approach. Our experiments demonstrate that HueLoc attains a location-mapping accuracy of 100% and achieves decimeter-level localization precision with a moving object in uncontrolled lighting conditions. Moreover, these unique signatures can be combined with other RF-based technologies to enhance their localization accuracy. As an example, this article details the integration of Bluetooth features with light signatures using a three-stage incremental learning approach. The experimental results show that this fusion method significantly improves Bluetooth localization by over 75%, overcoming challenges associated with severe indoor multipath and achieving highly precise location accuracy within decimeters.**

***Index Terms*—Bluetooth low energy, color sensors, machine learning, passive visible light positioning (VLP).**

I. Introduction

Spatial awareness in mobile objects (e.g., robots) is increasingly crucial in the evolving smart Internet of Things (IoT) ecosystem, especially for intralogistics operations, which include transporting goods, managing inventory, handling materials efficiently, and distributing products [1]. Achieving greater precision in these tasks hinges on accurate localization. In this context, visible light positioning (VLP) has emerged as a prominent solution. Over the past decade, VLP has attracted attention for its precise location awareness capabilities, leveraging the directive nature of light. Additionally, VLP has several advantages: it uses a wide unregulated spectrum, avoids multipath propagation issues, ensures security, and employs cost-effective, low-power receivers such as photodetectors (PDs). These characteristics allow for both cost efficiency and high accuracy in geolocation, making VLP a favored choice in smart IoT applications [2].

VLP technology typically employs light sources, such as light-emitting diodes (LEDs) as transmitters, with a camera or PDs serving as receivers. A significant challenge in commercializing these systems is the need for modulated light sources, which requires integrating an additional control unit into the lighting system for transmitting location beacons [3]. This modification necessitates changes to the existing lighting infrastructure. Alternatively, there are passive VLP systems in the literature that do not require light source modulation [4]. These systems perform localization by extracting intrinsic light features that act as location beacons. However, most rely on cameras as receivers and multiple PDs to realize the system. For example, LiTell [5] harnesses the characteristic frequency of fluorescent lights (FLs) to create a low-cost passive VLP system. Yet, determining this frequency is feasible only in FLs and requires high-resolution cameras, which are not cost-effective. Additionally, the use of power-intensive cameras as receivers limits their application in certain low-power IoT devices. Another approach, iLAMP [6], extracts the spatial-radiation pattern, or the intensity distribution across the light source. Nevertheless, this method also depends on power-consuming cameras and ambient light sensors, complicating the passive VLP system.

In this article, we introduce HueLoc, building upon our previous work HueSense [7]. HueLoc represents an innovative approach to passive VLP, aiming to identify unmodified light sources and leverage them for localization. HueLoc utilizes off-the-shelf power-efficient color sensors as receivers and by employing unmodulated and unmodified existing LED lights as anchors, HueLoc addresses several commercialization challenges in VLP systems. Our objective with HueLoc is to develop a passive VLP system that is low-power, cost-effective, easy to integrate, and computationally efficient, making it ideal for IoT devices needing ubiquitous location awareness and tracking. Our key observation lies in that LEDs emit slightly different color spectra that are indistinguishable to the human eye but can be detected by color sensors. This means that a light source can be uniquely identified by its spectrum without the need for modulation or modification.

Fig. 1 illustrates the motivation behind HueLoc. The key challenge lies in effectively and efficiently distinguishing among unmodulated lights so that no additional light

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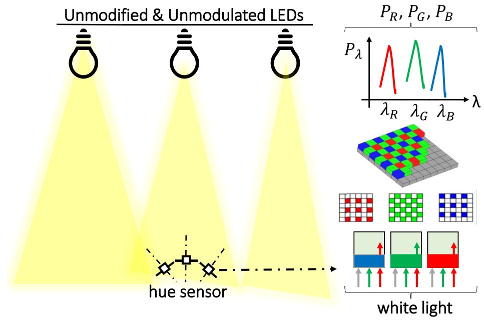

Detected wavelength (λ_m) at the maximum spectral power in the wavelength range of 400-500 nm for four commodity LEDs of the ***same model and brand****.*

LED	L1	L2	L3	L4
λ_m **(nm)**	448.0312	455.2858	450.2281	456.1662

Fig. 1. Motivation of HueLoc: LEDs have slightly different color spectrum that human eyes cannot distinguish. Still, the differences can be detected by color sensors, indicating that an LED can be uniquely identified by its spectrum without the need to modulate it.

identification (ID) information is required to be sent. While this approach can be implemented using PDs, it requires multiple PDs with spectral sensitivity wavelengths corresponding to the dominant colors present in the light source. In contrast, HueLoc uses *single-pixel* color sensors to extract the light hue-spectrum, which are cheaper and power-efficient, lowering the system complexity. However, the simplicity of using single-pixel detectors and the spectral information introduces a new challenge: it is hard to perform localization using standard methods like channel-based or angle-based techniques [3], [8]. This difficulty arises because the light intensity at dominant wavelengths varies with the distance or angle from different LEDs, making traditional distance or angle calculations unreliable. To overcome this, we propose a regression-based learning approach. This method learns how light intensity at certain wavelengths changes with distance or angle for different LEDs, enabling accurate localization. To our knowledge, this is the first passive VLP system that uses single-pixel color sensors to map light hues for location services. We outline our key contributions as follows.

1) We present a novel method for efficient *passive* light feature extraction, using *single-pixel color sensors* to identify dominant wavelengths in white LEDs.
2) This technique is further leveraged to distinguish unmodified and unmodulated white LEDs, a vital initial step in providing spatial awareness services to mobile objects.
3) We utilize this feature to provide accurate localization to mobile objects with a proposed dual approach that integrates classical mathematical methods with a contemporary, learning-based regression model.
4) We experimentally test HueLoc through a full-fledged implementation on the Arduino boards equipped with sensor modules, in a 25m^2 uncontrolled LED network. Our results show HueLoc achieves 100% light ID precision and decimeter-level localization accuracy.
5) Additionally, we exploit this feature to augment BLE-based localization systems. Our proposed three-stage incremental learning fusion method integrates HueLoc features with BLE's received signal strength (RSS) data. With testing in the same LED network, now supplemented with BLE nodes, our approach achieves decimeter-level localization with a mean localization error of about 12 cm, demonstrating a significant improvement–over 75% compared to existing SOTA BLE techniques.

Manuscript Outline: This article is structured as follows. Section II reviews existing VLP systems. Section III details HueLoc's light attributes and their extraction. Section IV explores using these attributes for light ID, mobile object localization, and BLE localization improvement. Section V evaluates our methods in a dense VLP testbed, discusses limitations, and suggests future work. This article concludes in Section VI.

II. Background

VLP systems can be broadly classified into two main categories: 1) active VLP and 2) passive VLP systems. In active VLP, the transmitter sends modulated information encoding the location beacons to the receiver [9]. Conversely, in passive-VLP, the transmitter does not transmit any location beacon information; instead, intrinsic properties of the light are studied to uniquely identify the light source and map the unique ID to the installed locations to offer location services [4]. LiTell [5] was the pioneering work in the passive-VLP category, utilizing unmodified FLs as location landmarks and commodity smartphones as light sensors. LiTell's method is limited to FLs, which restricts its usage in current indoor environments [5], [10]. It also requires high-resolution back cameras with RAW output, and it suffers from a high-misidentification rate (around 40%). A similar feature is extracted by Pulsar [11] for LEDs, using dual-PDs, but the system demands specially designed detectors with a specific field of view (FOV), making it a complex VLP system. Auto-LiTell [12] also employs a similar feature as LiTell [5], using a deep-learning model for ID only. However, the localization accuracy was not evaluated. In another work, iLAMP [13] extracts the spatial radiance pattern of the lights, i.e., the radiance intensity distribution across a light's surface, from images captured by a smartphone's camera. This approach is power-hungry and achieved close to 100% accuracy in identifying the location but was tested only under one FL, with the target placed at 25 random spots, achieving 3.5-cm accuracy.

The other passive-VLP works reported in the literature are primarily focused on occupancy determination and gesture monitoring [14], lacking the capability to provide location services to mobile targets. On the other hand, most of the active VLP systems are designed for localization and navigation services, but they often require modifying the lighting unit- cost ineffective and rely on power-hungry cameras (power hungry) as receiving units, resulting in significant processing latency [15]. While camera-based systems [16] are more readily available compared to photodiode-based alternatives [17], they necessitate additional units on the receiver side. Nevertheless, the cost of adding extra sensing units to the receivers is considerably lower than the expense

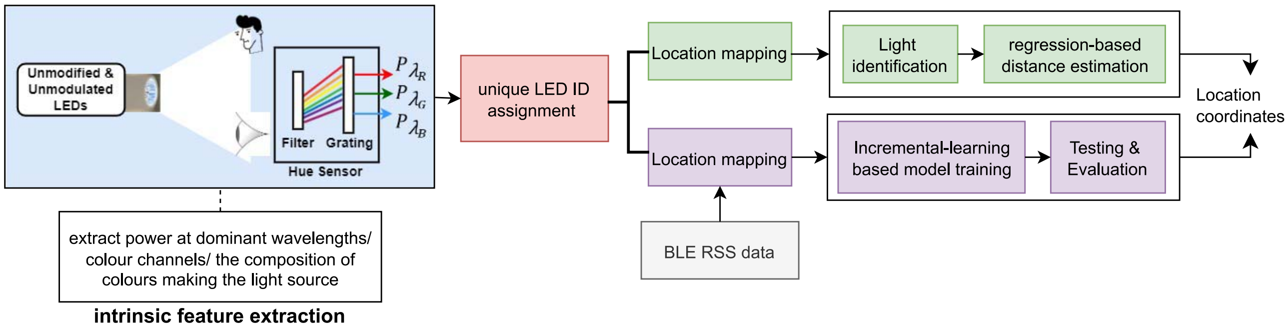

Fig. 2. Overview of HueLoc, which uses off-the-shelf color sensors to uniquely identify white LEDs based on dominant wavelengths for location services. It also integrates these unique IDs with BLE RSS measurements to enhance BLE localization.

of changing lighting units. Our research, HueLoc, aligns with the objectives of passive-VLP systems, aiming to eliminate the need for altering existing lighting units, offering location services. Additionally, HueLoc offers the advantage of using cheaper, power-efficient color sensors and requires no strict arrangement of sensors, making them easily integratable with low-power IoT devices.

Machine learning-based systems have been proposed to enhance positioning accuracy in active VLP systems. Some studies [18] combine RSS with AoA information using a single LED for RSS, and a steerable laser to provide angle data, employing methods, such as decision trees, support vector machines, and neural networks (NNs). One approach [19], utilizes deep learning to analyze changes in light reflections, captured through variations in impulse responses, for object positioning without requiring an active receiver on the target. However, the method is limited to a single, fixed-height object and requires extensive training to adapt to impulse response changes, restricting its ability to track multiple objects or operate in real-time.

To address varying indoor environments, Hua et al. [20] proposed an unsupervised adversarial training method to improve the robustness of VLP systems under changing parameters like LED characteristics, light power, and environmental noise. Although promising, its performance in real-world scenarios with random light noise remains uncertain, and the model's computational complexity could challenge real-time adaptation. DIALux [21] offers a simulation-based approach for generating training data, reducing the need for large-scale real-world data collection. However, it relies heavily on vendor-specific LED information and results in uneven errors across the room. Another method [22] employs a sigmoid function to preprocess RSS data, enhancing lower signal strengths in low-light conditions to improve positioning accuracy. This approach, however, is tested only in a small, controlled environment (50 cm × 50 cm), limiting its practical applicability.

Overall, these systems often require modifications to the lighting infrastructure and focus on static targets, overlooking real-world challenges, such as ambient noise, low-light conditions (dark spots), mobile targets, and the need for minimal infrastructure changes and training data. Our research in HueLoc aims to address these issues and provide a more adaptable ML-based VLP system.

III. HueLoc Design

In this section, we provide an overview of the HueLoc system. We describe how to distinguish between unmodulated LEDs and present our technique for extracting and analyzing their unique features (referred to as *light ID*) using color sensors.

A. Overview

Fig. 2 represents the block diagram of HueLoc, where the first step is to extract the intrinsic features from LEDs, specifically the power at dominant wavelengths, and then assign a unique identification as explained in Section III-B. The defined LED signatures can provide location awareness to the target device, i.e., to convey the area information- under which LED they are present. Furthermore, these signatures can be employed to determine the precise location coordinates within the specified area using the approach outlined in Section IV-B. Additionally, the unique signatures can be combined with the BLE RSS measurements from BLE anchor nodes to enhance their localization performance. The fusion approach for achieving this enhancement is detailed in Section IV-B.

B. Preliminary

The wavelength of light emitted by LEDs, and thus its color, depends on the materials forming the LED chip. Due to unavoidable manufacturing imperfections, e.g., the variations in the phosphor coating thickness and the nonuniformity, different optical properties of the light originate, such as the change in radiant flux and color temperature. These imperfections make LEDs' radiated power for particular wavelengths different, which motivates the design of HueLoc.

In the case of white LEDs, the three dominant emitted wavelengths are λ_R, λ_G, and λ_B at the red (R), green (G), and blue (B) channels, with more contribution from the B and G channels, compared to the R channel. To generalize this property, we use the spectrometer[1] to extract the LED spectrum from four different white LEDs of the same model and brand in a room. The resultant experimentally extracted spectrum is shown in Fig. 3, which plots the moving average of intensity to remove unwanted peaks/intensity fluctuations due to ambient noise. We capture the spectrum for different LEDs within

[1]https://www.thorlabs.com/newgrouppage9.cfm?objectgroup_id=3482

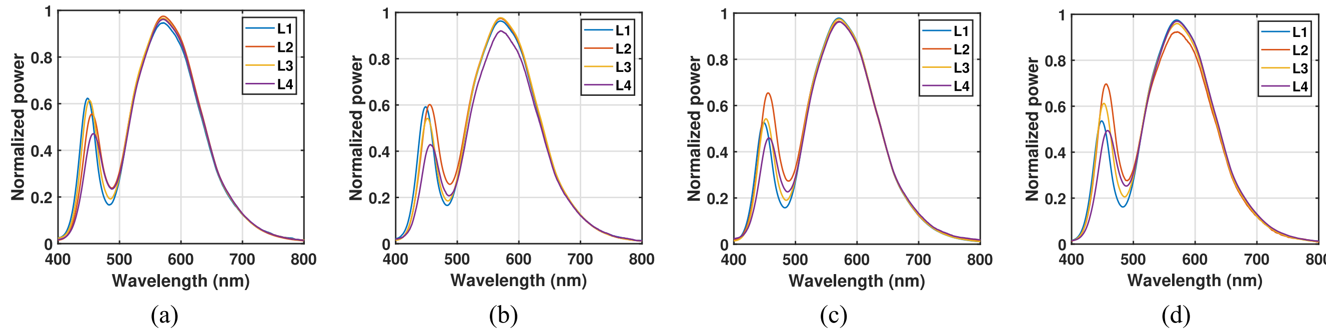

Fig. 3. Detected LED spectrum using high-spectrum resolution spectrometer at different incident angle (θ). (a) $\theta = -45°$. (b) $\theta = -30°$. (c) $\theta = 30°$. (d) $\theta = 45°$.

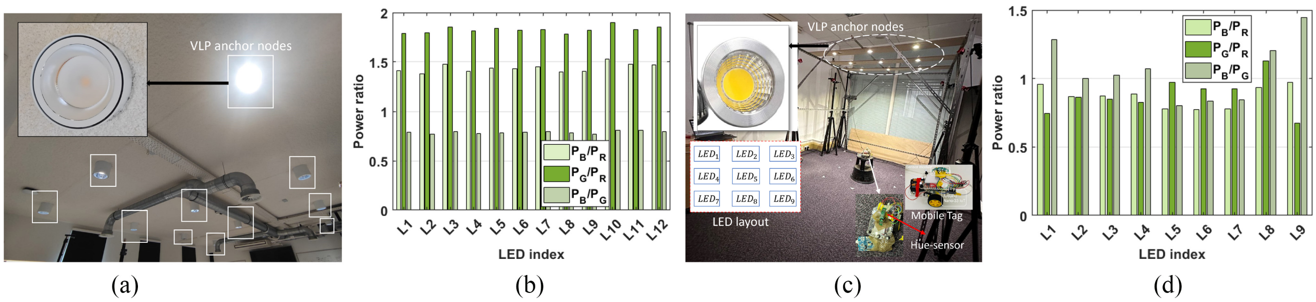

Fig. 4. Experimentally obtained RGB power ratios for two sets of off-the-shelf LEDs: (a) The first set of LEDs used in the existing lab environment; (b) The RGB power ratios measured for the set in (a); (c) The second set of LEDs in a lab testbed; (d) The RGB power ratios obtained for the set in (c). In both cases, the LEDs are of the same model and brand within each environment.

their FOV, showing that each LED has a unique hue-spectrum and verifying that the spectrum properties remain constant at different positions. Moreover, in our HueSense study [7], we showed the statistical difference in the spectrum series by conducting a t-test.

Furthermore, more variations in the light spectrum can be observed around 450 nm wavelength. The emitted wavelength corresponding to the maximum power peak in this wavelength range of 400–500 nm is also different for different lights. Fig. 1 shows the maximum power peak wavelengths for four lights in this wavelength range (the maximum power variation region). This interesting feature can be used as the ID of LED lights. However, the extraction is feasible only using the spectrometer, an expensive solution and difficult to fit into small IoT devices. In Section III-C, we will present an alternative cost-effective approach to realize the hue properties of LED lights using off-the-shelf hue sensors.

C. Light ID—Distinguishing LEDs Through Their Hidden Color Features

An important hidden feature, which can be derived from Fig. 3, is that the ratio of power at dominant wavelengths (i.e., λ_R, λ_G, and λ_B, in case of the white LED lights) at different positions remains constant. The principle of HueLoc is to extract the power around the dominant wavelengths present in the unmodulated white LED bulbs and use this hidden feature as a discriminative feature among lights. To obtain this hidden feature, small off-the-shelf hue sensors[2] can be used to extract the spectral power at λ_R, λ_G, and λ_B wavelengths. This type of sensor can be easily deployed into the tiniest IoT devices, and they can directly extract the dominant wavelengths of white LEDs. For example, Fig. 4 shows the experimentally obtained power ratios for two different off-the-shelf LED models. The first set, consisting of 12 LEDs, is installed in our lab, while the second set includes 9 LEDs from our lab test environment, with both sets tested under Line-of-Sight (LoS) conditions. The average marginal differences are in the range of ≈ 0.672 to 1.897, with larger differences observed between LEDs from different manufacturers due to variations in their production processes.

Proposed LED's Light ID: Based on the captured power ratio values, we propose to construct the ID L_i of the ith LED using the following tuple:

$$L_i : \left\langle \frac{P_{B_i}}{P_{G_i}}, \frac{P_{G_i}}{P_{R_i}}, \frac{P_{B_i}}{P_{R_i}} \right\rangle \tag{1}$$

where $i = \{1, \ldots, N\}$, N is the total number of LEDs; P_{R_i}, P_{G_i}, and P_{B_i} are the received spectral power at R, G, and B channels, respectively. In reality, these IDs can be calculated from the measurements of the LEDs and are stored in a database for location services.

However, how do we differentiate between light sources with the same power ratios of R, G, B channels or approximately negligible difference between the power ratios? To eliminate this problem, we employ *multiple sensors with different incident angles*. This approach facilitates the sensor modules to have the information of neighboring LEDs that will help with the ID. The design is shown in the bottom part (top of mobile tag) of Fig. 7, where sensors S2 and S3 are

[2]https://www.hamamatsu.com/eu/en/product/optical-sensors/photo-ic/color-sensor/rgb-color-sensor.html

inclined at 45-degree angles with respect to the center sensor S1. The optimum inclination angle can be found based on the separation between different light sources and link distance. However, with HueLoc, the motivation is to design a flexible solution which works for different illumination infrastructures. We choose the inclination angle as 45 degrees as the minimum separation between light sources is usually a few meters. The three sensors extract the hue-spectrum properties of the nearest LED and its neighboring LED lights, provided these LED lights are in the sensor's FoV. To elaborate, the power ratio observed at the central sensor (S1), which is aligned parallel to the LED, typically captures the highest power from the target LED. Conversely, the other sensors (S2 and S3), depending upon their FoVs, may detect power ratios that are influenced by neighboring LEDs or a combination of signals from both the target and adjacent LEDs. This arrangement enables the differentiation of LEDs that may appear identical when only a single sensor is used. Even if the power ratios observed by the S1 sensor are the same for identical LEDs, the measurements from the other sensors will differ, allowing for unique identification.

Algorithm 1 ID

1: **procedure** LED LIGHT ID ASSIGNMENT
2: For each sensor $S_j, j \in \{1, 2, 3\}$, extract the power at R, G, B wavelengths for each light $L_i, i \in \{1, 2, \ldots, N\}$ in the database as $P_{R_{ij}}$, $P_{G_{ij}}$, $P_{B_{ij}}$, and store the ID as

$$L_{ij} : \left\langle \frac{P_{B_{ij}}}{P_{G_{ij}}}, \frac{P_{G_{ij}}}{P_{R_{ij}}}, \frac{P_{B_{ij}}}{P_{R_{ij}}} \right\rangle$$

3: **procedure** LIGHT IDENTIFICATION
4: Let $\tilde{L}_{kj}$ denote the measured ID values at location k.
5: At current location k, calculate the Euclidean error as $E^i_{kj} = \sqrt{(L_{ij}[1] - \tilde{L}_{kj}[1])^2 + (L_{ij}[2] - \tilde{L}_{kj}[2])^2 + (L_{ij}[3] - \tilde{L}_{kj}[3])^2}$
6: Find the minimum error value for each sensor as

$$D_{kj} = \min_i E^i_{kj}$$

and store the corresponding argument where the minimum is obtained as M_{kj}.
7: For location k, find the predicted values P_k as
8: **if** $M_{k1} \neq M_{k2} \neq M_{k3}$ **then**
9: $P_k = \arg\min_j D_{kj}$
10: **else**
11: $P_k = M_{k1}$

IV. HueLoc Inner Workings

This section describes how HueLoc determines the light IDs and details methods for the exact location. Then, we present a use case of HueLoc – enhancing RF localization performance.

A. Determining the Light Identification

HueLoc employs the procedure outlined in Algorithm 1 for passive positioning, which involves identifying LED lights using detected hue properties. The sensor module, as depicted in Fig. 7, can be positioned atop a target device, such as a robot, equipped with a stored LED ID database. This database allows the system to estimate the device's location within a room, specifically under which LEDs it is moving. This estimation is done by finding the minimum Euclidean error between the stored LED ID values and newly measured power ratios at dominant wavelengths, denoted as $\tilde{L}$. Once the LED unit is identified, we can pinpoint the target's accurate location by focusing on the area lit up by that specific LED unit. The steps to accomplish this are explained in Section IV-B.

B. Performing Accurate Localization

The light ID is unique and independent of the position under the LED, i.e., remains constant with the link distance and at different FoV, as proved in our previous paper [7]. This feature can only be used for the LEDs' identification but for localization—the feature should vary either w.r.t distance or angle. In classical RSS methods, the received power values are used to determine either the distance or angle w.r.t LED to determine the receiver location w.r.t the LED, i.e., by utilizing the channel model [11], [23]. However, due to the usage of single pixel color sensors the distance cannot be directly determined from the received power. Moreover, the power received at dominant wavelengths at a fixed distance under different LEDs is different, making it challenging to perform localization with channel models [3]. A direct mathematical relation for power variation with distance and angle cannot be determined from the IDs as they differ for different LEDs (HueLoc's principle). To solve this, we propose a combined classical and learning-based approach for accurate localization.

In simple words, after the successful ID, we use sensors S2 and S3, to further reduce the search area to half or a quarter of the detected area; subsequently, the next step involves determining the target's position within this reduced area, which is determined using regression-based learning methods. Our training involves the model being exposed to power values at dominant wavelengths generated by a *single* LED at varying distances from its central position, to learn the behavior of power with distance. One significant challenge associated with learning approaches is the necessity to train the model across all possible locations within a specified area, a process that is both cumbersome and time-consuming. However, in HueLoc, we streamline the training process by focusing on learning the variations in power relative to distance under a *single* LED. This simplification is based on the theoretical assumption that the intensity behavior in relation to distance remains consistent across all LEDs. The distinctive factor, however, lies in the varying power levels at dominant wavelengths, which differ between LEDs even at the *same distance* and ideal channel conditions. This power disparity between LEDs at the same link distance necessitates adjusting or compensating for the power levels of LEDs other than the one used during training, before feeding the data into the trained model for distance prediction. The detailed steps to address this are outlined in Algorithm 2, and the proposed method is analyzed below. A visual illustration of the process is provided in Fig. 5.

Localization Approach: After successful light ID, the detection/search area is restricted to the region where the light falls on the ground. Just for simplicity, assume a circular light emission pattern falling on the ground and the goal is to

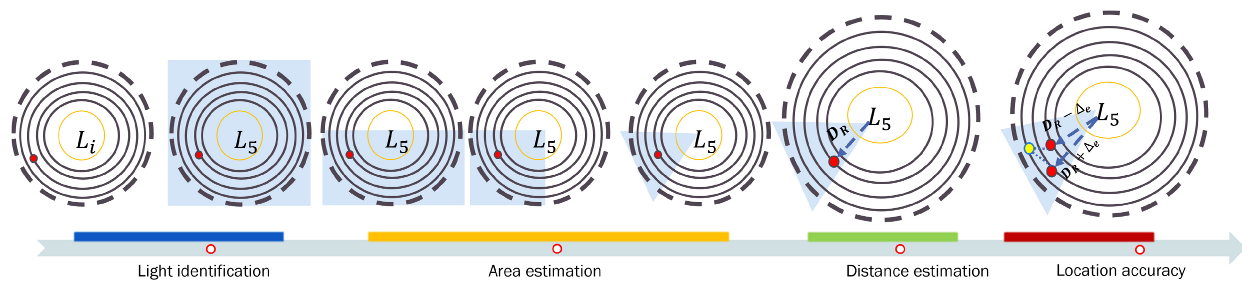

Fig. 5. Steps in HueLoc localization process—The circle depicts the emission pattern of light, with the shaded area indicating the potential target location zone.

determine the receiver's position within this circle (see Fig. 5). Below are the steps in HueLoc to determine the target position.

Step 1 (Determine the Forward Direction of the Mobile Target):

1) Choose the forward sensor (e.g., S2) to identify the forward direction of the mobile target.
2) Determine the minimum Euclidean error in light fingerprints from neighboring lights using the procedure described in Algorithm 1. This narrows the search area for the receiver's position to half the detection area, i.e., a semi-circle aligned with the forward direction of the light receiver (third circle from left in Fig. 5).

Step 2 (Determine Which Side/Direction of the Light Source, the Target Is Present): Repeat step 1 to determine which side of the light source the receiver is located. This step helps to determine whether the receiver is on the left or right side of the light source within the semi-circle search area (fourth circle from left in Fig. 5). Please note that in this case, the search for the minimum Euclidean error with the installed lighting unit is limited to only the light units present around the detected light source in step 1. This focused search approach helps streamline the localization process and increases efficiency by considering only the relevant light units in the vicinity of the detected light source. The detected area in this step can further be reduced to one by eight (fifth circle from left in Fig. 5) by repeating steps 1 and 2 provided the neighbor LEDs are present. If a wall is present on the side of the searching area, this step would be omitted. The identified quarter search area would be used for further position estimation.

Step 3 (Determine the Precise Location): To determine the mobile target's precise location relative to the detected LED, HueLoc employs a regression-based learning model, M, as detailed in Algorithm 2. This model calculates the distance between the target device and the LED and then utilizes the LED's known coordinates to ascertain the target's location coordinates.

C. Enhancing RF-Based Localization

We harnessed RF features from our BLE-based localization system, BLoB [24], to enhance its localization precision down to the decimeter level. BLE is particularly advantageous due to its low cost, low-power consumption, and ease of deployment, making it ideal for large-scale localization tasks in energy-constrained environments. Moreover, the direction-finding capabilities introduced in BLE 5.1 significantly enhance positioning accuracy, which is especially beneficial for indoor settings [25]. By integrating BLE with HueLoc, we create an energy-efficient system that leverages the latest advancements in BLE technology to provide more accurate and reliable localization.

Our methodology incorporates an incremental learning (IL) approach to fuse data from these two distinct technologies. Incremental learning, as used in this research, pertains to a machine learning paradigm where the model continually learns

Algorithm 2 Regression-Based Learning Method

Require: Sensor S1, LED L_{train}
Ensure: Trained localization model M
Data Collection:
for each location (x_i, y_i, z_i) under L_{train} **do**
  Measure light features $P_{R_i}, P_{G_i}, P_{B_i}$ using S1.
Model Training:
Let $\mathbf{P}_i = [P_{R_i}, P_{G_i}, P_{B_i}]^T$ be the feature vector for x_i.
Define d_i as the distance or angle from L_{train} to (x_i, y_i, z_i).
Train model M:$\mathbf{P} \mapsto d$ with $\{(\mathbf{P}_i, d_i)\}$.
Model Evaluation:
Calculate test error Δ_e using 80% of data for training and 20% for testing.
Model Storage:
Archive M for runtime use.
Runtime Localization:
On detecting L_{test}, extract $\mathbf{P}^{ID}_{L_{\text{test}}}$.
Compute $\Delta\mathbf{P} = \mathbf{P}^{ID}_{L_{\text{train}}} - \mathbf{P}^{ID}_{L_{\text{test}}}$.
Adjust $P_{\text{adjusted}} = P_{L_{\text{test}}} + \Delta\mathbf{P}$.
Use $M(P_{\text{adjusted}})$ to predict D_{R}.
Final Location Determination:
Find location minimizing Δ_e within $D_R \pm \Delta_e$ range.
Assign coordinates based on minimized Δ_e and known L_{test} position.

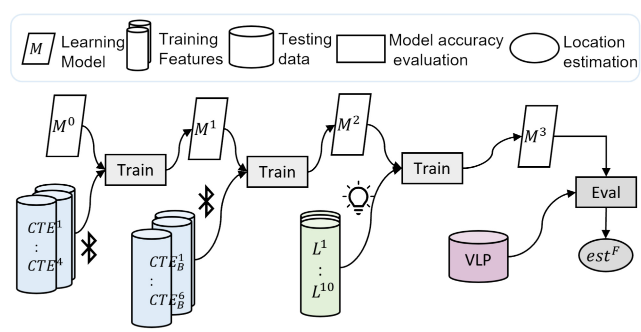

Fig. 6. HueLoc-fusion model: A 3-stage incremental learning method to blend BLE and VLP features for enhanced localization.

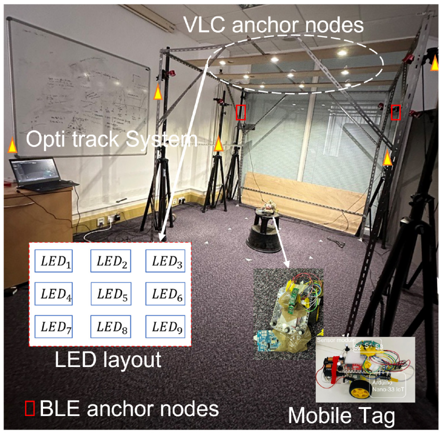

Fig. 7. HueLoc experimental testbed and implemented prototype: A robot equipped with three hue sensors and a BLE receiver to collect light and BLE features, transmitting them over a WiFi network for localization.

and adapts as new data becomes available. This approach empowers the model to continuously refine its knowledge, opening up new possibilities for joint RF- and VLP-based localization. The fundamental assumption underlying IL in this study is that, despite their differences, both RF and optical or VLP modalities convey information about the signal-location relationship or distribution within a specific indoor environment.

Furthermore, IL could reduce the feature interference of different sources, so in one stage, the model learning will only be affected by one signal feature. The architecture of the proposed approach is shown in Fig. 6. This is an advanced version of our architecture proposed in [26] with improved localization performance. In the training phase, the first two steps incorporate features from BLE, specifically those extracted from the signal and beating spectrums [24]. As proved in BLoB [24] studying the beating spectrum can enhance the localization performance, we proved here that by training the model in an IL approach the model performs better. This approach helps the deep NN (DNN) model to improve its comprehension of location-related features. In the third stage, the trained model continues to enhance and increment its localization capabilities by leveraging the light signature features. The optical features are more fine-tuned; however, missing locations are more frequent in this due to the blockage of light signal frequently. The evaluation of localization performance can be conducted at either the BLE or VLP stage. In Section V, we will present the experimental setup and results.

V. Performance Evaluation

This section introduces our prototype of HueLoc, assessing its ability to passively identify LEDs and for accurate locations. We focus on evaluating HueLoc's localization performance and enhancement for RF-based localization.

A. Implementation

Prototype: The prototype we developed is shown in Fig. 7. It serves to experimentally, analyze and test the performance of HueLoc. We implement HueLoc using three HAMATASU color sensors and integrate the sensors with an Arduino board to simultaneously collect the R, G, and B channel power, i.e., P_R, P_G, and P_B, respectively, from each sensor. The employed sensors are power efficient and can run on a 3.3-volt (V) battery. The integration of sensors with Arduino is done using the repository[3] defined for `TCS34725`-color-sensors, with modifications in alignment with our sensors in the MATLAB Simulink. The Arduino board is `33-Nano IoT`[4] with integrated WiFi capability, compact and power-efficient runs on 3.3 V, perfect for low-power IoT devices. The designed Simulink model is deployed on the Arduino board, which will collect and transmit the extracted light information over the WiFi network to the host machine. The host machine runs the algorithm used for light ID and localization in MATLAB. Further, to provide the ground truth location information against which we compare our analysis, we employ a highly accurate Optitrack system. Moreover, to test the performance of the fusion approach, we added the BLE receiver in the same prototype, with four BLE anchor nodes tuned at frequencies f_1, f_2, f_3, f_4 and collected the data from both technologies simultaneously. The BLE stack protocol is acquired from our paper [24].

Testbed: We built a dense LED network with 9 off-the-shelf white LEDs covering an area of 10 m^2, refer to Fig. 7. The interseparation distance between the LEDs is $\approx$ 55 cm from the center of each LED to create interference as the FOV is 36°. For the BLE technology, we added four BLE devices close to the LED network setup, at the four corners spanning an area of 25 m^2.

B. HueLoc Localization Performance

We will initially showcase the results of our regression-based learning algorithm's efficiency by training it with a single LED and testing it under both the same and different LEDs. This demonstrates that our approach necessitates training with just one LED, effectively capturing power variations at dominant wavelengths with distance for all LEDs. We collect the data by placing the sensor module at various fixed locations within the LED's FOV, collecting more than 500 samples. We employ an 80% (training) and 20% (testing) data split ratio. Additionally, we collect unseen data from a different LED for testing under varying LED conditions. Fig. 8(a) shows our results, demonstrating 75% of the localization under the decimeter level for both the cases, i.e., when we use the testing data (same LED) and data from new LED. The mean generalization error is $\approx$ 7 cm. It is worth noting that even when testing under different LED the localization results obtained are similar, which validates the proposed approach.

Moving Object: Next, we will test the localization performance of HueLoc with a moving target, in which the first step is to determine under which light the target is moving and then determine the location coordinates. We use our prototyped robot shown in Fig. 8(b) and move it from LED "LED3" to "LED7" following an L shaped path to determine first the correct LED. Please note the LED numbers are provided here

[3]https://github.com/adafruit/Adafruit_TCS34725
[4]https://docs.arduino.cc/hardware/nano-33-iot

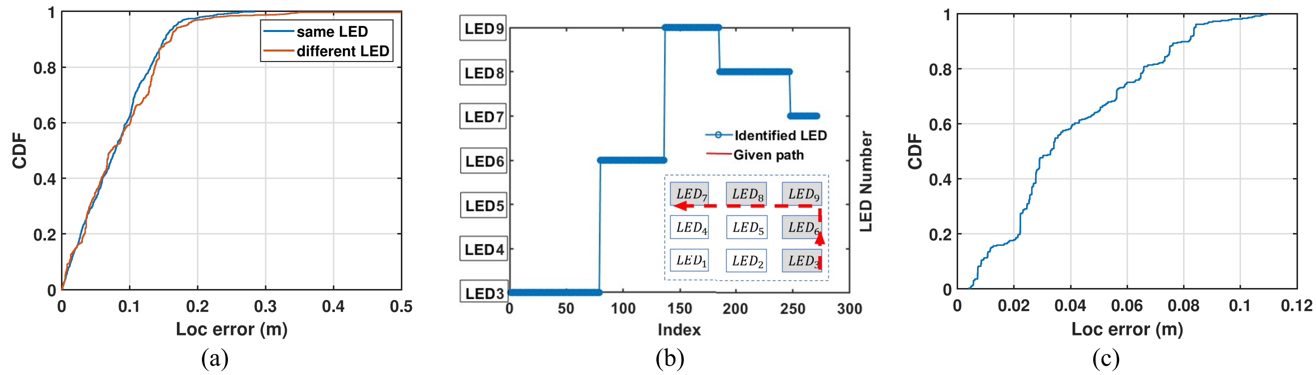

Fig. 8. HueLoc performance analysis. (a) Distance estimation error. (b) Light ID accuracy. (c) Localization accuracy.

just for differentiation between the LEDs. The sensor module collects the power values and transmits the collected light hue information to the system. We run the MATLAB code for light ID and localization on the system, which has the data stored of light's IDs collected during the light ID collection phase and the light installation map. We followed the procedure described in Algorithm 1 to identify the true LED under which the robot is moving and using Algorithm 2 to determine the coordinates. The robot is moved from LED3 toward LED7 [robot trajectory shown in Fig. 8(b)]. The results can be seen in Fig. 8(b), demonstrating 100% light ID accuracy. We also determined the localization coordinates using Algorithm 2, and compared them against the ground truth to determine the error. We present the results statistically by plotting the CDF of the localization error, shown in Fig. 8(c), where 90% of the errors are within decimeter-level, evading the proposed technique's validity.

Furthermore, Table I presents a comprehensive performance comparison of our findings with various SOTA approaches. It is important to note that the design goals and novel features of different passive VLP systems vary significantly [2], [4]. The unique characteristics of these systems, including differences in design objectives, experimental areas, and lighting conditions, make direct comparisons challenging due to the lack of a common benchmark. Therefore, to address this, we have outlined key features, novelties, and testing conditions, such as the size of the testing area, whether experiments conducted in controlled environments (i.e., without ambient noise or shadows), consideration of low-light conditions (dark spots), and mobile object tracking. Achieving high-localization accuracy is relatively straightforward, but the conditions and parameters used to achieve it are crucial. These parameters are essential to demonstrate the practical applicability and advantages of the designed systems in real-world environments.

For example, the systems [27], [28] provides remarkable localization accuracy (<2 cm); however, this accuracy is achieved within a small area, with no moving targets involved, and under controlled lighting conditions. Additionally, the system [28] requires a complex PD structure to attain this level of accuracy in a confined 50 cm × 50 cm area. In contrast, HueLoc has been tested in various environments, including corridors and testbeds, with varying lighting conditions and involving a mobile target.

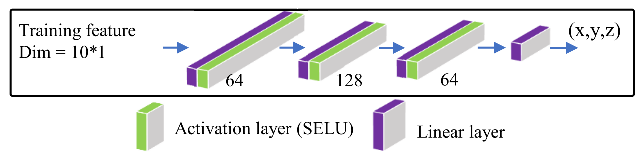

Fig. 9. Designed DNN architecture in HueLoc.

Other ML-based systems, such as those in [18], [19], [20], and [29], are currently limited to simulated environments, which restricts their practical applicability. Moreover, these systems involve an intensive training phase and require computationally expensive resources. HueLoc adopts a hybrid and computationally efficient localization approach, using regression-based learning for distance estimation and requiring limited training under a single LED.

Moreover, to address low-light conditions (dark spots), HueLoc operates in hybrid mode with BLE, offering dual benefits: enhancing VLP performance in low-light and shadowed areas while improving BLE localization. This hybrid enhancement includes a training phase, which may be further reduced in the future with advanced methods, such as hyperparameter tuning for optimal efficiency [30]. A comprehensive performance comparison is presented in Table I. Next, we demonstrate how HueLoc enhances BLE-based localization accuracy.

C. Enhancing BLE Localization

We are using the machine learning approaches especially DNNs to improve the BLE localization by fusing the data from both technologies. The architecture employed for this purpose is shown in Fig. 9. The DNN model adopted in HueLoc is a fully connected NN, whose architecture is shown in Fig. 9. The input is a $4 \times 1(f_1, f_2, f_3, f_4)$, $6 \times 1(f_1 - f_2, f_2 - f_3, f_1 - f_3, f_1 - f_4, f_2 - f_4, f_3 - f_4)$ vector for BLE, and $10 \times 1(P_{B_i}/P_{G_i}, P_{G_i}/P_{R_i}, P_{B_i}/P_{R_i}, P_{G_1} - P_{R_1})$ vector for VLP (please refer [26] for more details). The output is the estimated location coordinates (x, y, z). SELU is adopted as the activation function in the layers between input and output. First, we collected the data simultaneously from both technologies considering the locations directly under the LEDs with no ambient light source, low-light conditions (near the walls), and blocking of the sensor (due to human or testbed

TABLE I
PERFORMANCE COMPARISON OF THE SOTA TECHNIQUES WITH HUELOC

System	Testing environment						
	Area	Sensors	Controlled environment	Modified LEDs (high cost)	Dark spots	Mobile target	Accuracy
LiTell [5]	office, parking lot, grocery store	camera	N	N	N	Y	90.3% identification accuracy
Luxapose [15]	71.1 cm ×73.7 cm	camera	N	Y	N	Y	decimeter-level
LiTalk [16]	single LED with 70 cm link distance	camera	N	Y	N	N	1.97 cm- distance estimation
Pulsar [11]	corridor, aisles	dual PDs	Y	N	N	N	centimeter-level
Litell-v2 [12]	office buildings, malls, parking lots	camera	N	N	N	N	≈ 100% light identification
PassiveVLP [2]	linear path (2.5m inter-node distance)	PDs	Y	Y	N	Y	centimeter-level (trajectory)
BeaconVLP [27]	1m x 1m (various heights)	camera	Y	Y	N	N	1.17 cm at 2 m, 1.00 cm at 1.5 m height
[28]	50 cm × 50 cm	PD	Y	Y	N	N	sub-centimeter accuracy
ML- VLP [29]	5m × 5m (simulated)	PDs	Y	Y	N	N	0.88 cm average error
passiveML [19]	5m × 5m (simulated)	PDs	Y	Y	N	N	30 cm (high SNR, large training set)
AdVLP [20]	6m × 5m (simulated)	PDs	Y	Y	Y	N	<20 cm
DIALux [21]	2m × 1.55m (simulated, real-world)	PDs	Y	Y	N	N	10.5 cm (real data), 11.1 cm (simulation)
[31]	3m × 3m	PDs	Y	Y	Y	N	0.25m
[22]	unit cells: 50 × 50 cm horizontally, 95–135 cm vertically	PDs	Y	Y	Y	N	centimeter-level
[18]	5m × 5m (simulated)	PDs, laser	Y	Y	N	N	0.0386 m
HueLoc	corridor, 10 m^2 (testbed)	colour sensors	N	N	Y	Y	100% LED detection, decimeter-level localization

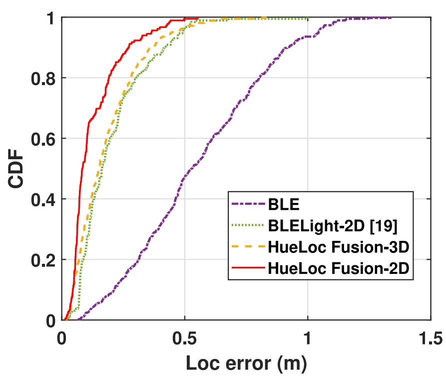

Fig. 10. HueLoc: Fusion performance analysis.

metals). Our data collection aims to achieve two goals: first, to show that BLE performance will enhance and second, to demonstrate how VLP technology can overcome limitations like low-light conditions or blocked light signals. A total of 5 datasets are collected with different target heights, comprising 8813 samples for the BLE and 4776 samples for the VLP. We adopt an 80%-20% data split, allocating 80% for training and the remaining 20% for testing. We statistically evaluate the performance of our proposed approach, i.e., the three-stage incremental learning approach and compare it against our system [26]. Further, showing the performance of the alone BLE localization system to demonstrate the improvement in localization performance. Fig. 10 reveals that 50% of the 2-D localization error is under decimeter-level, with 90% under ≈ 20 cm achieving a mean 2-D localization error of 12 cm. Moreover, the 3-D achieved mean localization error is 18.4 cm. Compared to the BLE localization system, the proposed approach has demonstrated an increment of > 75%, due to the more fine localization data from the VLP measurements. Moreover, the proposed approach offers ≈ 37% performance increment against SOTA system [26].

D. Limitations and Discussion

1) Model Training: Training a model to learn power changes at dominant wavelengths with just one LED might affect accuracy due to varying power levels across LEDs. An alternative, as mentioned in [32], uses unique LED features across an area, improving performance but increasing data collection time. While this technique could enhance model performance, it necessitates extended data collection times proportional to the area's size. Nonetheless, HueLoc achieves decimeter-level accuracy efficiently without extensive data needs. Furthermore, power variation at different wavelengths is affected by the material's reflection properties at those wavelengths. Unlike the experiments in [32], with participants in white clothing, HueLoc's testing was conducted independent of clothing color, showing that adjusting color sensors can mitigate reflections from specific colors or materials. Further detailed studies could be pursued in the future.

2) Low-Light Conditions: VLP systems, particularly passive-VLP, encounter challenges in ambient and low-light conditions. This article demonstrates that combining different technologies makes HueLoc a viable solution for real-world applications. Notably, HueLoc operates effectively in various scenarios without the need for RF fusion, especially in contexts where continuous tracking is unnecessary. In HueLoc fusion, the integration of additional light features with BLE localization results in a performance improvement of 1.75-fold. However, changes in location necessitate model retraining due to the variability in LED features. Despite this, such an approach enhances existing RF-based localization solutions without incurring additional transmitter costs. Moreover, HueLoc's integration surpasses current SOTA methods, such as [33] and [34], by achieving decimeter-level accuracy and introducing unique data integration. A distinctive feature is leveraging data from LEDs within existing lighting infrastructure, combined with BLE features, offering a novel approach. This method distinguishes HueLoc from typical SOTA implementations [35], which often limit tests to a few LEDs under controlled conditions.

3) ID Normalization: The LED IDs in HueLoc are constructed using the power ratios of RGB components ($[P_{B_i}/P_{G_i}]$, $[P_{G_i}/P_{R_i}]$, $[P_{B_i}/P_{R_i}]$), which capture the relative hue differences between LEDs and remain robust to external

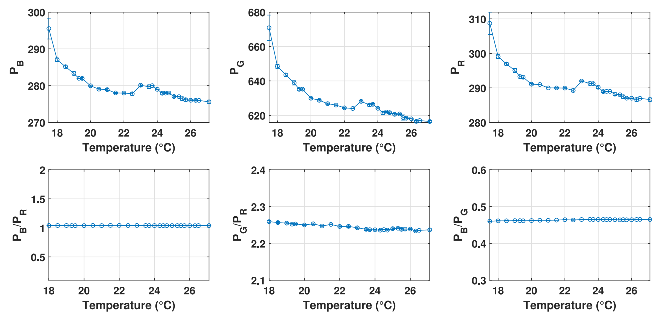

Fig. 11. Impact of room temperature.

factors like distance and angle. These ratios inherently act as a form of normalization, reflecting the intrinsic hue properties rather than absolute power values. While normalizing the ID components could further standardize the vectors and potentially reduce minor variations in Euclidean distance calculations, our experiments (please refer Fig. 7) indicate no significant impact on identification accuracy without normalization. Future work may explore normalization as a way to enhance system performance in environments with extreme variations in LED brightness or color characteristics.

4) Impact of Temperature and Aging: To investigate the impact of temperature on the extracted power ratios at the RGB channels, we conduct an experiment where the temperature varies from 17.5 °C to 27 °C. The results, as shown in Fig. 11, indicate a clear decreasing trend in power as the temperature increases. However, despite this reduction in power, the extracted ratios (features) exhibit only minor fluctuations, with no significant patterns or variations due to temperature changes. Additionally, considering that most public buildings maintain tightly regulated indoor temperatures between 19 °C and 23 °C, we focus on this range and find that the standard deviation of the features remains small, fluctuating between 0.0006 and 0.0018. These variations are unlikely to affect the system's performance in typical indoor environments.

Over a nearly half-year observation period, the power ratios of the LEDs used in the experiment show no significant changes, suggesting that the system continues to perform reliably even with potential LED deterioration. In the unlikely event of substantial long-term LED deterioration leading to identification mismatches, affected LEDs can be isolated or replaced to ensure continued accuracy.

VI. Conclusion

This manuscript introduces HueLoc, a passive VLP system that leverages the hue spectrum of unmodulated LEDs for ID, utilizing a single-pixel hue sensor. We have successfully demonstrated the system's capability to distinguish between various unmodulated LED lights by exploiting their inherent color properties. The extracted salient features are subsequently utilized to provide location-based services, achieving decimeter-level accuracy in localization. Moreover, we demonstrate that combining these features substantially enhances RF-based localization systems, improving their effectiveness by a notable 75%.

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