HueSense: Featuring LED Lights Through Hue Sensing

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ABSTRACT

Visible Light Positioning (VLP) has been prevalent in providing high-precision localization systems in the past decade. However, the commercial availability or usage is still limited primarily due to the requirement of changing the existing lighting infrastructure. In this paper, we propose HueSense, an alternative technique to develop a passive VLP system by extracting light-emission intrinsic features, such as dominant colours present in the white LED light. The method can eliminate the need to change lighting-infrastructure, and only uses cheaper and power-efficient off-the-shelf hue sensors. Our experiments demonstrate that HueSense can achieve a location-mapping accuracy of 80.14% with a moving robot in uncontrolled lighting environments.

CCS CONCEPTS

• **Computer systems organization → Embedded systems**; • **Networks → Location based services**.

KEYWORDS

Passive visible light positioning, Colour sensors.

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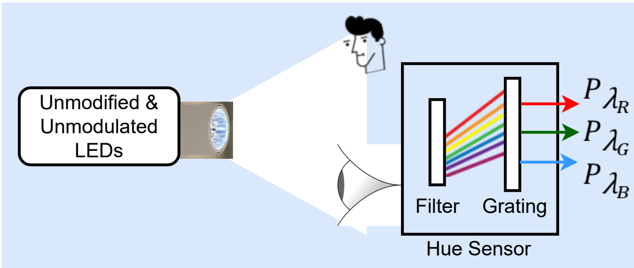
1 INTRODUCTION

Spatial awareness among robots is a key requirement in today's smart Internet of Things (IoT) world [1, 2]. Location tracking is needed for performing multiple intralogistic tasks such as moving goods and inventory control, for efficient material handling or goods distribution, among others. The location awareness services provided by visible light technology, termed Visible Light Positioning (VLP), have attracted much attention in the past decade because of its enormous advantages compared to conventional Radio Frequency technology, including the use of a wide unregulated spectrum, multipath-free propagation, security and inexpensive receivers, i.e., photodetectors (PDs), and for providing high accuracy geolocation [4, 6, 7]. VLP has a broad range of potential applications, such as service robot navigation that may clean, monitor or assist in homes, offices, retail, warehouse and hospital environments.

The technology employs light sources such as Light Emitting Diodes (LEDs) or fluorescent lights as a transmitter and a camera or PDs as a receiving device. However, the commercial availability of such systems is mainly hampered by the requirement of modulated light sources which in turn requires changes to existing lighting infrastructure [5]. An alternative, passive VLP systems which do not modulate the light source exists in the literature [3, 4, 6]; however, most of them use the camera as a receiver and multiple PDs to realise the system. LiTell [9] harnesses the intrinsic characteristic frequency of fluorescent bulbs to enable a low-cost passive VLP system. However, the determination of characteristic frequency can only be realised in fluorescent bulbs using high-resolution cameras, which is not a cost-effective solution. Further, power-hungry cameras as a receiver limit their usage in some low-power IoT device applications. A similar feature extracted by Pulsar [10] for LEDs rather than fluorescent bulbs using dual-PDs, but the system requires specially designed detectors with a specific Field Of View (FOV). Another solution, iLAMP [8] extracted the spatial-radiation pattern, i.e., the intensity distribution across the light body,



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

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

to discriminate light sources. However, this method also relies on power-consuming cameras and ambient light sensors, making it a complex passive VLP system.

In this paper, we propose HueSense, a novel passive VLP system for light identification which can be further used for providing location services to low-power IoT devices using off-the-shelf power-efficient colour sensors as receivers. Additionally, HueSense employs the unmodulated and unmodified existing LED lights as anchors, removing some barriers to commercializing VLP systems. With HueSense, our goal is to design a low-power, cheap, easily integrable and computationally inexpensive passive VLP system for IoT devices to provide ubiquitous location tracking. *Our key observation lies in that LEDs have slightly different colour spectrum's that the human eye cannot distinguish. Still, it can be detected by colour sensors, indicating that a light source can be uniquely identified by its spectrum without needing to modulate or modify it.* Figure 1 presents the motivation of HueSense. This approach could be realised using PDs. However, multiple PDs required with spectral sensitivity wavelength correspond to the dominant colours present in the light source.

In HueSense, we rely only on *single-pixel* colour sensors to extract the light hue-spectrum. The key challenge lies in effectively and efficiently distinguishing among unmodulated lights so that no additional light identification (ID) information is required to be sent. In HueSense, we lower the complexity by using power-efficient and cheaper single-pixel light colour sensors as detectors. To the best of our knowledge, this is the first passive VLP system which employs single-pixel colour sensors to extract the light hue-spectrum and perform the light mapping. We summarize our contributions as follows.

(1) A novel power-efficient and cost-effective *passive* light feature extraction method enables *single-pixel colour sensors* to extract the power of dominant wavelengths in the white LEDs.
(2) Further exploitation of this feature to differentiate between unmodified and unmodulated white LED light sources for light identification, which is a vital initial step in providing spatial-awareness services.
(3) Preliminary experimental validation of HueSense based on a full-fledged implementation on the Arduino boards for light identification.

2 HUESENSE DESIGN

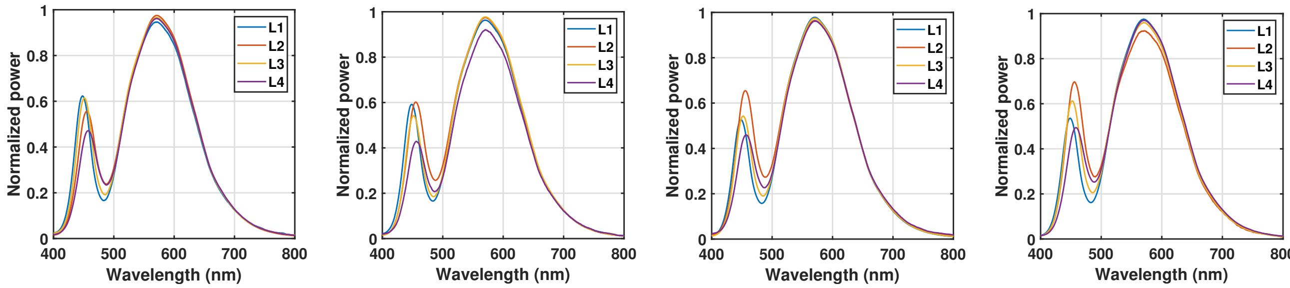
In this section, we first present the principle of the proposed passive light identification method, answering the question of how we can effectively differentiate between unmodulated LED light sources. Then, we present the technique to extract and analyse those hidden discriminating features (termed *light ID* in this paper) using cheap colour sensors.

2.1 Preliminary

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

In the case of white LED light, the three dominant emitted wavelengths are λ_R, λ_G, and λ_B at Red (R), Green (G), and Blue (B) channels, with more contribution from B and G channels, compared to the R channel. To generalise this property, we use the spectrometer[1] to extract the LED light spectrum from four different white LED lights in a room. The resultant extracted spectrum is shown in Figure 2, 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 their FOV, showing that each LED has a unique hue-spectrum and verifying that the spectrum properties remain constant at different positions. Moreover, to show that the spectrum series are statistically different, we perform the t-test[2] on the L1's spectrum mean with zero mean difference as the null hypothesis. Table 1 shows the

[1] https://www.thorlabs.com/newgrouppage9.cfm?objectgroup_id=3482
[2] A t-test is a type of inferential statistic used to determine if there is a significant difference between the means of two groups, which may be related in certain features.



(a) $\theta = -45°$ (b) $\theta = -30°$ (c) $\theta = 30°$ (d) $\theta = 45°$

Figure 2: Detected LED spectrum using high-spectrum resolution spectrometer at different incident angle (θ).

Table 1: Performed t-test on LED L1 spectrum with other LEDs (L2, L3) obtained at different spectrometer positions (P1-P5) within the FOV of the LEDs.

Position, LEDs	P1, L1-L2	P1, L1-L3	P2, L1-L2	P2, L1-L3	P3, L1-L2	P3, L1-L3	P4, L1-L2	P4, L1-L3	P5, L1-L2	P5, L1-L3
h-value	0	1	1	1	1	1	1	1	1	1
p-value	0.4914	3.6448e-05	1.1421e-05	5.9617e-10	2.8785e-36	0.0024	3.4147e-281	4.0482e-289	5.0735e-101	3.0002e-06

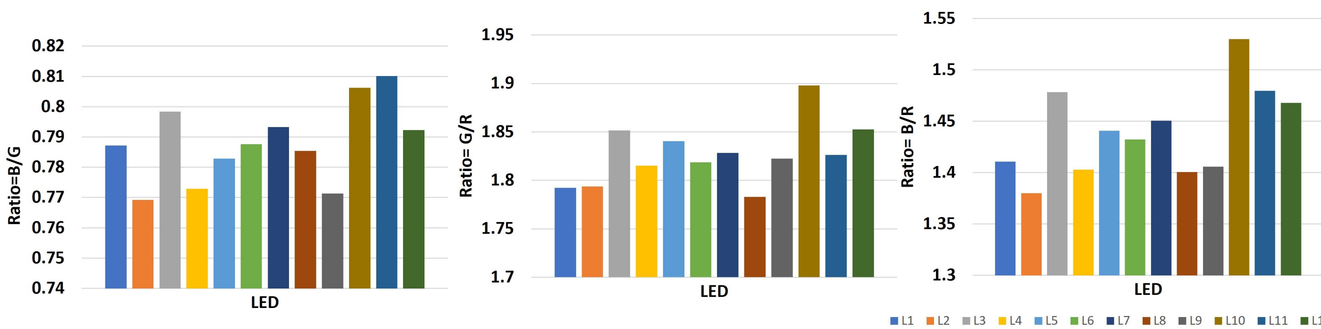


Figure 3: RGB power ratio comparison among 12 commodity LEDs of the same model & brand.

results. These p-values confirm the statistical significance and validates the principle of HueSense.

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. Figure 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 the next section, we will present an alternative cost-effective approach to realise the hue properties of LED lights using off-the-shelf hue sensors.

2.2 Light ID: Distinguishing LEDs Through Their Hidden Colour Features

An important hidden feature, which can be derived from Figure 2, 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 HueSense 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 sensor[3] 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 lights from LED bulbs. For example,

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

Algorithm 1 Light identification with multiple sensors.

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

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

procedure LIGHT IDENTIFICATION
  Let $\tilde{L}_{kj}$ denote the measured ID values at location k.
  At current location k, calculate the Euclidean error as $E^i_{kj} = \sqrt{(L_{ij}[1]-\tilde{L}_{kj}[1])^2 + (L_{ij}[2]-\tilde{L}_{kj}[2])^2 + (L_{ij}[3]-\tilde{L}_{kj}[3])^2}$
  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}.
  For location k, find the predicted values P_k as
  if $M_{k1} \neq M_{k2} \neq M_{k3}$ **then**
    $P_k = \arg\min_j D_{kj}$
  else
    $P_k = M_{k1}$

Figure 3 shows the obtained power ratios for 12 LEDs under Line-of-Sight (LoS) scenarios in a lab environment.

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 $i = \{1, \cdots, N\}$, 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, B channels, respectively. In reality, these IDs can be calculated from the measurements of the LEDs and are stored in a database for future light identification during testing.

Light identification with multiple sensors. The sensor module can be placed on top of robots with the stored LED ID database information that can estimate their locations in a room, i.e., under which LEDs they are moving. This estimation can be done by finding the minimum Euclidean error between the stored LED ID values and newly measured power ratios at dominant wavelengths, denoted as $\tilde{L}$.

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 neighbouring LEDs that will help with the light identification. The design is shown in top part of Figure 4, where sensors S2 and S3 are inclined at 45-degree angles with respect to the centre sensor S1. The optimum inclination angle can be found based on the separation between different light sources and link distance. However, with HueSense, 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 neighbouring LED lights, provided these LED lights are in the sensor's FoV. The procedure for passive positioning by identifying the LED lights using the detected hue properties is presented in Algorithm 1.

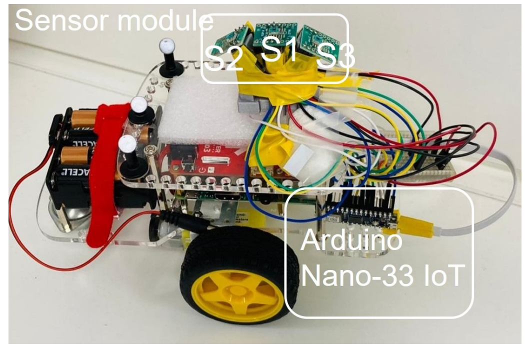


Figure 4: Our implemented prototype: robot equipped with three hue sensors to collect light features and send them over a WiFi network for light identification.

3 IMPLEMENTATION

In this section, we present the implementation of HueSense.

Our implemented prototype is shown in Figure 4. We implement HueSense using three HAMATASU colour 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[4] defined for TCS34725-colour-sensors, with modifications in alignment with our sensors. The Arduino board is 33-Nano-IoT[5] with integrated WiFi capability, compact and power-efficient runs on 3.3 V, perfect for low-power IoT devices. The light identification analysis is done in MATLAB, and the Arduino board is flashed with a Simulink model.

We also integrate the robot odometry with the Arduino board to provide the ground truth positions to investigate the performance of HueSense for moving objects for light identification. Further, the extracted data is transmitted over the WiFi network to a laptop to perform light identification analysis.

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

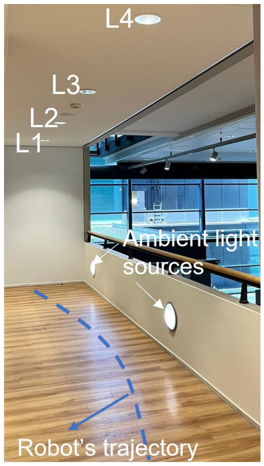


Figure 5: Experimental setup at our premises.

4 PRELIMINARY RESULTS

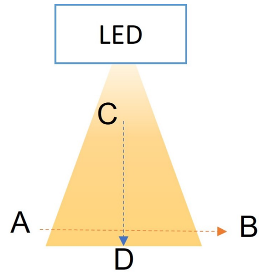
In this section, we present the preliminary results of HueSense for passively identifying the LED lights with a robot under both static and moving scenarios. The experiments are performed in an uncontrolled lighting environment, the corridor at our premises. The experimental setup is shown in Figure 5.

4.1 Impact of Distance and Incident Angle

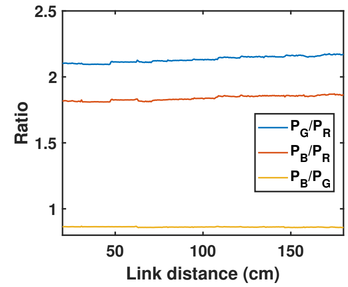
First, we evaluate if the spectral power ratio values remain constant with varying the distance and incident angle with respect to the light source. As shown in Figure 6a, we perform the evaluation using one LED and measure the spectral power at different incident angles (by moving the sensor from position A to position B, at a distance of 1 m) and various distances (by moving a sensor from position C to position D). Figure 6b and Figure 6c show the measurement results. It can be observed that the ratio of the dominant wavelengths remains approximately constant (± 0.01) over different LED positions and different incident angles, which propel the average ratio value of the spectral power at the dominant wavelength to be considered as LED ID.

4.2 Light Identification

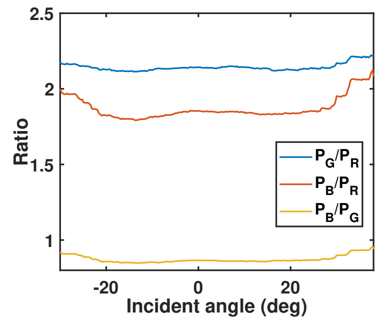
Static scenario: The goal of HueSense is to passively differentiate between light sources based on hue properties. We first evaluate the performance of HueSense under static scenarios, i.e., when the sensor is not moving and located exactly below the light source. We assess this in different environments, e.g., lab, corridor. The identification results obtained with four LEDs are shown in Figure 7 and Figure 8, where the LEDs with the lowest Euclidean distances are interpreted as the identified corresponding LED. We can see that the light identification performance of HueSense is 100%.



(a) Setup



(b) Measured power ratio vs. distance



(c) Measured power ratio vs. incident angle

Figure 6: Impact of distance and incident angle on the power ratio.

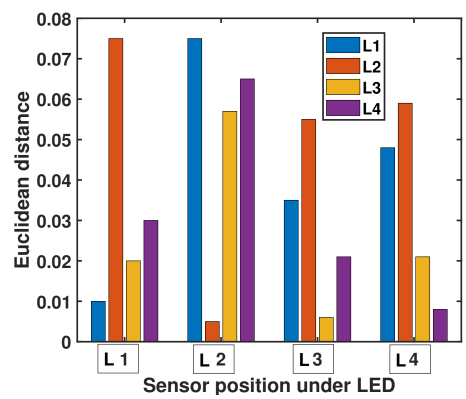


Figure 7: Light identification under the LEDs in an uncontrolled lighting environment.

Moving scenario: For testing the performance with a moving target, a robot, as shown in Figure 4 carrying the sensor module, is used for evaluation. The benefit of using the robot is that it can provide the ground position while moving based on the odometry analysis. The robot is moved from LED1 towards LED4 (robot trajectory shown in Figure 5). The sensor module collects the power values and transmits the collected light hue information to the system. We run the MATLAB code for light identification on the system, which has the data stored of light's IDs collected during the ID

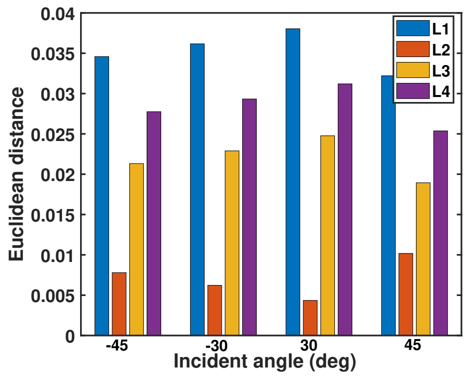


Figure 8: Light identification at different incident angles in an uncontrolled lighting environment.

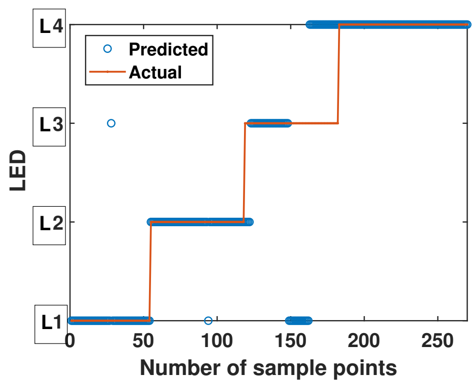


Figure 9: Light identification accuracy with a moving robot in an uncontrolled lighting environment.

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.

With our approach Algorithm 1, we successfully identified the correct LED ID with 80.14% accuracy with a moving target. The results are presented in Figure 9. The robot projected a curved path instead of a straight line due to the friction errors in the wheel. This makes the sensor module predict incorrect LED ID when under the LED L3. At this position, the robot moves closer to the wall, and the ambient light source introduces noise, making the identification difficult.

4.3 Potential Application

HueSense can be employed for providing spatial awareness, location-based services to humans, and Automated Guided Vehicles such as robots, to name a few. When we use VLC for passive localization, the first step in performing that is to know the LED IDs, the initial requirement that HueSense is fulfilling.

5 CONCLUSION

To our knowledge, HueSense presents the first passive VLP system to extract the hue-spectrum of unmodulated LEDs for light identification using the single-pixel hue sensor. We have successfully implemented and shown that different unmodulated LED lights can be distinguished by exploiting their intrinsic colour properties. We believe the salient features of HueSense will help promote the usage of VLP in a wide range of location-based applications such as autonomous robot navigation and indoor navigation.

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