**Spectral-Loc: Indoor Localization Using Light Spectral Information**

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Fig. 1. Experimental evidence of the fact that even under the same light source, different light spectral distribution can be observed at different indoor locations. (a) Different indoor materials have different reflectance curves [16], (b) two spectral sensors on the same wall but facing different views, (c) spectral information sensed by the two sensors on two different days.

For indoor settings, we investigate the impact of location on the spectral distribution of the received light, i.e., the intensity of light for different wavelengths. Our investigations confirm that even under the same light source, different locations exhibit slightly different spectral distribution due to reflections from their localised environment containing different materials or colours. By exploiting this observation, we propose **Spectral-Loc**, a novel indoor localization system that uses light spectral information to identify the location of the device. With spectral sensors finding their way into the latest products and applications, such as white balancing in smartphone photography, **Spectral-Loc** can be readily deployed without requiring any additional hardware or infrastructure. We prototype **Spectral-Loc** using a commercial-off-the-shelf light spectral sensor, AS7265x, which can measure light intensity over 18 different wavelength sub-bands. We benchmark the localization accuracy of **Spectral-Loc** against the conventional light intensity sensors that provide only a single intensity value. Our evaluations over
two different indoor spaces, a meeting room, and a large office space, demonstrate that the use of light spectral information significantly reduces the localization error for the different percentiles.

CCS Concepts: • Human-centered computing → Ubiquitous and mobile computing.

Additional Key Words and Phrases: Indoor localization, Spectral information, Ambient light

ACM Reference Format:
Yanxiang Wang, Jiawei Hu, Hong Jia, Wen Hu, Mahbub Hassan, Ashraf Uddin, Brano Kusy, and Moustafa Youssef. 2023. Spectral-Loc: Indoor Localization Using Light Spectral Information. Proc. ACM Interact. Mob. Wearable Ubiquitous Technol. 7, 1, Article 37 (March 2023), 26 pages. https://doi.org/10.1145/3580878

1 INTRODUCTION

Indoor localization plays a critical role in many application scenarios, including healthcare centers, robot navigation, shopping malls, and smart buildings to name a few. Recent market research estimates the global indoor localization market to be USD 40.99 billion by 2022 [26]. The significance of this technology has attracted massive research efforts over the past decades, but a ubiquitous solution that would work accurately and reliably in all indoor scenarios is yet to be found [24].

Among many radio-based localization options, WiFi-based indoor localization is the most extensively studied, mainly due to its ubiquity. However, the ultra-sensitivity of WiFi signals to the surrounding environment often makes them unreliable. In addition, a high density of WiFi access points is required to achieve good accuracy, which may not be available in many scenarios. Finally, radio frequency may face safety concerns in some critical environments like hospitals, mines, and military compounds, where it may interfere with sensitive devices, machinery, or instrumentation.

As lighting infrastructure is already there in indoor environments, there is a growing interest to use light for indoor localization. Light is more stable compared to radio and has a much higher density of deployments compared to WiFi. Most existing light-based localization solutions, however, rely on modifying the light emitting diode (LED) so that the lighting infrastructure can transmit useful beacons or some spatial information to the receivers for localization [20, 23, 44, 46]. Although modified LED-based techniques can achieve precision and reliable localization, they are limited to LEDs only and incur retrofitting costs as well, which can be a barrier to wide deployments.

For light-based localization to become ubiquitous and practical, we need solutions that can work with all types of lights, LED or otherwise, and without requiring any modifications or modulations of the light. However, indoor localization without modulating or modifying the light source is extremely challenging because the receiver can neither identify the light sources, nor it can benefit from any spatial light transmitting patterns anymore. Zhang and Zhang [48] used the unique resonance frequencies of fluorescent lamps to identify them without requiring any modifications, but they do not work for other types of lights such as LED. Since light intensity changes with the distance from the light source, Zhao et al. [49] investigated the potential of light intensity to realize indoor localization under arbitrary unmodified lighting infrastructure. However, they discovered that light intensity from a single location has limited performance, hence they proposed a system, called NaviLight [49] that uses light intensity values from a series of locations within a trajectory of a walking person for accurate localization. However, trajectory-based localization works only when the user is moving. Accurately fingerprinting single locations under arbitrary unmodified lighting infrastructure remains an open problem.

To address this challenge, we propose to utilize light spectral distribution, i.e., the intensity of light for different wavelengths within the visible spectrum, as a means to fingerprint a given location. The intuition behind this is that different locations are surrounded by different environmental objects, such as walls with different colors, doors with different materials, and so on, which have different light reflection properties. Figure 1(a) shows that walls, bookshelves, and metal cabinets, which are typically found in indoor environments, have quite different
spectral reflectance curves. This suggests that, even under the same lighting condition, different locations of the room may exhibit different spectral distributions, which we experimentally verify in Figure 1(b) and (c). As a result, compared to the scalar light intensity value, the use of spectral information may have the potential to achieve more accurate localization under the same lighting conditions.

We have implemented our proposed spectral information-based localization system, called Spectral-Loc, using a commercial off-the-shelf (COTS) light spectral sensor, AS7265x [35], which can measure light intensity over 18 different wavelength frequencies or sub-bands. Our results confirm that light spectral information can be useful for indoor localization and can significantly outperform solutions that utilize only light intensity. Given that spectral sensors are becoming a commodity and are finding their way in consumer mobile devices [9, 10] for supporting a variety of other applications, Spectral-Loc can be readily deployed without requiring any additional hardware or infrastructure.

The contributions of this paper can be summarised as follows:

- To our best knowledge, Spectral-Loc is the first system that uses ambient light spectrum information for location fingerprints. The method works without requiring modification of the existing lights and works with commonly available light sources.
- We evaluated Spectral-Loc under two real environments, a small meeting room, and a large office room, and compared it against prior work, i.e., the light intensity-based methods such as EHAAS [40]. We show that the spectrum fingerprints not only improve the localization accuracy but are also more robust to environmental variations.
- We studied the impact of different factors, such as body orientations, light interference, daytime sunlight, and the varying number of spectral sub-bands, on the performance of Spectral-Loc. Our results show that spectral information significantly improves localization accuracy compared to intensity information.

The rest of the paper is structured as follows. The necessary hypotheses that must hold for spectral information to be used for indoor localization are identified and tested in Section 2. We introduce the background model for spectra-based localization in Section 3. The design of Spectral-Loc is discussed in Section 4, followed by its evaluation in Section 5. We discuss the limitations of our implementation and related work in Sections 6 and 7, respectively, before concluding the paper in Section 8.

2 HYPOTHESES TESTING

In Figure 1, we provided evidence that two locations in the same room under the same lighting condition can observe distinct spectral distributions, which laid the motivation for this paper. In this section, we aim to show that light spectral information not only can be an indicator of location, but it can be a more reliable indicator than the basic intensity information. We achieve this by first identifying the necessary hypotheses that must hold, and then testing them through extensive measurements. We start with a brief background on light intensity and light spectral information.

2.1 Background

Light intensity is a scalar-valued function that returns a single value indicating the received radiant flux per unit area [8]. Light spectrum, on the other hand, is about the color light separation through dispersion systems such as prisms, gratings, or the monochromatic light pattern sequentially arranged by wavelength (or frequency). In addition to the overall radiant light power in the area, spectral information also includes the composition of that light source, i.e., the intensity of monochromatic light at each wavelength. In other words, the light spectrum represents the strengths or weights of different wavelengths or frequencies.

While expensive and bulky equipment is required to obtain the full distribution of light over all wavelengths, the recent arrivals of commodity spectral sensors, such as AS7265x that we used in this study and the ones included...
in some of the latest smartphones [9, 10], can measure received light over a small set of wavelengths. These sensors are low-cost low-power devices that have been introduced in the market relatively recently. Some of the applications of these spectral sensors include product authentication, anti-counterfeiting, portable spectroscopy, adulteration detection, horticultural and specialty lighting, and material analysis [35].

2.2 Hypotheses

We identify three hypotheses that must hold if spectral information is to be useful (i.e., provide effective features) for indoor localization:

(1) For typical indoor environments, the spectral distribution of received light is location dependent.
(2) Light spectral information is a more reliable indicator of location than basic light intensity information.
(3) For a given environment and lighting condition, the spectral distribution of received light at a given location is stable, i.e., preserved over time.

2.3 Measurement and Testing

We started by asking a subject to wear an AS7265x at the left wrist and stand for 40 seconds at each of the 10 different locations in a small meeting room. Sensor values from the 18 sub-bands were collected using an Arduino Uno at a rate of 1Hz, which provided 40 18-dimension vectors of spectral data for each location (the details of the room and the sensor implementation will be discussed in Section 5).

Using t-distributed stochastic neighbour embedding (t-SNE) [41], we visualize the data, along with the corresponding intensity data that is derived by summing up the 18 spectral values together, in a 2D plot in Figure 2. The figure shows that spectra data can indeed differentiate different indoor locations (Hypothesis 1) by representing them as clearly separated clusters in Figure 2(a). Furthermore, the euclidean distances between any two clusters in Figure 2(a) is significantly larger than those in Figure 2(b), which indicate that spectral information is a more reliable indicator of location than basic light intensity information (Hypothesis 2). Finally, we repeat the experiment under the same lighting condition on three other days and observe in Fig. 3 that the average t-SNE cluster distances do not change much between days (Hypothesis 3).
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Fig. 3. Averaged distance between t-SNE clusters for spectrum information on different days.

3 SPECTRA-BASED LOCALIZATION MODEL

3.1 Indoor Location Spectral Fingerprint

Modern buildings are usually equipped with multiple types of light bulbs for indoor lighting. Common lighting includes incandescent light bulbs (ICL), compact fluorescent lamps (CFL), and light-emitting diode (LED). Different indoor environments have different layouts, furniture, shadowing, scattering, and light source density and orientation. As a result, the light (intensity and spectrum) distributions in an indoor environment are not uniform. Therefore, ambient light intensity and spectrum information may produce stable and discriminative indoor location signatures. We denote the lighting condition in a 2D location \((x, y)\) as:

\[
L(x, y) = f(\phi),
\]

where \(\phi\) is the ambient light, and \(x\) and \(y\) are the location coordinates. Earlier work [49] has investigated the use of basic light intensity value as the indoor location fingerprints:

\[
L_i(x, y) = f_i(\phi),
\]

where \(f_i(\phi)\) is light intensity of the ambient light in location \((x, y)\), which can be decomposed as the energy summation of different light spectra:

\[
L_i(x, y) = f_i(\phi) = \int_\alpha^\beta (\phi),
\]

where \(\alpha\) and \(\beta\) are the starting and finishing light wavelength, respectively. Different light intensity sensors respond to different wavelength ranges and have different values for \(\alpha\) and \(\beta\), which are decided in the sensor manufacturing stage.

Instead of a single value \((L_i(x, y))\) that represents the total the energy between a certain wavelength range, i.e., between \(\alpha\) and \(\beta\) in Eq. (3), spectral sensor can return the energy levels of a number of sub-wavelength ranges (i.e., sub-bands):

\[
L_i(x, y) = f_i(\phi) = (\phi_i)_{i=1,2,...,N},
\]

where \(\phi_i\) is the energy in sub-band \(i\), and \(N\) is the number of sub-bands. For example, the COTS AS7265x spectral sensor, used in the Spectral-Loc prototype in this paper, supports \(N = 18\) sub-bands, ranging from ultraviolet (UV) light (i.e., 410 nm) to infrared (IR) light (i.e., 940 nm), with approximately 30 nm wavelength range in each.
sub-band. In essence, spectral sensors can measure finer grain ambient light information (e.g., the different colors of reflective objects such as walls) compared to the basic light intensity sensors.

By following the localization methodology proposed by Sen et al. in [34], we divide the indoor space in the granularity of 1m × 1m boxes (i.e., spots), and the spectra-based localization problem becomes

\[ P(x_i, y_i) = F(C|f_s(\phi)), \]

where \( P(x_i, y_i) \) is the predicted location coordinate, and \( C|f_s(\phi) \) is the real-time (current) spectral fingerprint observation. The prediction function \( F \) is produced automatically via machine learning training process based on historical spectral fingerprints, which will be discussed in detail later in Section 4.

3.2 Light Sources

As discussed in the previous section, there are three main types of light bulbs in the market: ICL, CFL, and LED. The ICL bulbs produce lights by heating a wire filament, which has a color closer to yellow. In contrast to ICL, CFL bulbs generate invisible UV lights by charging a mercury vapour, which hit the fluorescent coating in the tube to produce visible lights. Finally, LEDs are semiconductor-based light bulbs that release light when the electrons are combined with the electron holes. The energy states of electrons and electron holes in different semiconductor materials are different. The more the released energy, the shorter the wavelength of the emitted light. Because of their different mechanisms of light generation, the lights generated by different types of light bulbs have distinct patterns of spectrum distributions, which are shown in Fig. 4. Since light bulbs are relatively fixed in a given indoor environment, these distributions can be exploited by, both intensity and spectra-based, localization algorithms to produce unique location fingerprints (i.e., \( L_i(x, y) \) and \( L_s(x, y) \)).

![Different spectrum distributions from three common types of light bulbs.](image)

3.3 Light Reflection

Light reflection is a physical phenomenon that occurs when light enters from one kind of medium into another, and its propagation direction changes at the interface of the two media before returning to its original medium. The reflectance of materials indicates their effectiveness in reflecting radiant energy. Normally, the reflectance is related to the light’s incident angle, polarization, and wavelength (frequency). Specifically, the spectral reflection
curve describes the material’s reflection characteristics for different wavelengths, which can be formulated [15] as:

\[ R_\lambda = \frac{L'_\lambda}{L'_i}, \]

where \( R_\lambda \) is the reflectance in wavelength \( \lambda \), \( L'_\lambda \) is the spectral radiance of reflected light, and \( L'_i \) is of incident light.

For different materials and different colors, the reflectance is different. For example, the red interior wall has higher reflectance values for the red light range (622 ∼ 780 nm) and lower reflectance ratios for the rest. This imbalance indicates different objects will selectively absorb specific wavelengths of light, resulting in differences in the wavelengths of the reflected light, which is the reason human eyes and cameras can perceive different colors of objects. In the database [16], there are 1,294 types of opaque materials’ reflectance measured with spectrally-specific spectrophotometer sensing devices. The left subplot in Fig. 1 shows the reflectance curves of four classes of materials (i.e., bookshelf, metal cabinet, and two different colors of walls), which are commonly found in different indoor environments, from the database. The figure shows that their reflectance characteristics of them are significantly different from each other, which will produce non-identical reflections even with the same light sources.

![Spectral Sensor](image)

**Fig. 5. Illustration of light propagation.**

### 3.4 Impact of Location on Spectrum Readings

The ambient light measured by a spectrum sensor at a given location consists of two main components: direct lights from light sources (e.g., light bulbs) discussed in Section 3.2, and reflective lights from surrounding objects discussed in Section 3.3. For simplicity, let us assume there is one light source and one reflective object in the environment (see Fig. 5), and denote the direct and reflective lights by \( L_{LOS} \) and \( L_{RE} \), respectively, both of which follow the inverse-square law for visible light propagation. We can now derive the spectrum sensor’s measurements as:

\[
L_\lambda = L_{LOS}^\lambda + L_{RE}^\lambda
= \frac{L_b^\lambda}{a^2} + \frac{1}{c^2} \cdot R_\lambda \left( \frac{L_b^\lambda}{b^2} \right),
\]

where \( L_b^\lambda \) is the energy of the light source in wavelength \( \lambda \) in one of the directions, \( a \) is the direct distance between the light source and the sensor, \( b \) is the distance between the light source and the reflective object, and \( c \) is the distance between the reflective object and the sensor. Based on this simplified model, we can infer
that the spectrum measurements are likely to be different in different locations due to variations in the distance components, $a$, $b$, and $c$. We can further infer that the spectrum readings are affected not only by the light source, but also by the reflections.

To highlight the observation that reflections alone can change the measured spectrum distribution of lights at any given location, we deployed a number of spectral sensors (AS7265x) in a room with same light sources and collected spectrum measurements from them over multiple days. The sensors’ locations are shown in the middle subplot in Fig. 1, where different locations have different types of furniture. The right subplot in Fig. 1 shows that the spectrum distributions in different locations are indeed unique as these locations have furniture with different colors. Furthermore, the spectrum distributions are consistent over different days, which make them a good feature for fingerprint-based indoor localization.

It can be expected that the more variations of colors in a given environment, the more distinct the spectrum location signatures would be. We verify this by conducting a controlled experiment (see Fig. 6), where the walls of a 17\(m^2\) room are covered first with white fabric and later with a combination of different fabric colors. As can be seen in Fig. 7, the environment with a variety of colors produces more distinct spectrum fingerprints for the different locations. Given that typical indoor environments will have a variety of colors due to different materials and furniture, we can expect good spectrum fingerprints and high localization accuracy, which is confirmed later in Section 5 through extensive evaluations of two typical indoor spaces.

![Fig. 6. The controlled room with different colors of walls.](image)

4 SPECTRAL-LOC: LOCALIZATION BASED ON SPECTRUM INFORMATION

Spectral-Loc estimates a user’s current location in a room based on the measurements from spectrum sensors worn by her/him (see Figure 8). It has two phases: online training and offline location inferencing (see Fig. 9). In the online training phase, the spectral fingerprints are collected at different location points (“spots”) in a room. Then, the data, i.e., the fingerprints ($f_s(\phi)$) with their labels ($x, y$), are transferred to a server, which will train the localization module. In the offline testing phase, a new spectral fingerprint ($f_s(\phi)$) is measured by the spectrum sensor worn by a user in real-time and sent to the server, which will predict the user’s current location ($x, y$) based on the fingerprint and the trained localization model from the previous phase.
Normalization. Before we input the spectral sensor measurements (fingerprints, or $f_i(\phi)$) to the localization model, we perform the normalization on a measurement ($\phi_i$) by:

$$\phi_i^* = \frac{\phi_i - \phi_{\text{min}}}{\phi_{\text{max}} - \phi_{\text{min}}}$$  \hspace{1cm} (8)

where $\phi_{\text{max}}$ and $\phi_{\text{min}}$ are the maximum and minimum values in the fingerprint measurements respectively, and $\phi_i^*$ is the normalized measurement. As will be shown later in Section 5.2.5, the proposed normalization of spectral readings improves Spectral-Loc’s robustness against ‘unseen’ lighting conditions.

Localization neutral network model. Our model is based on Convolutional Neural Network (CNN) with an attention mechanism to consider the contributions from all possible locations. Fig. 10 shows the detailed network model architecture, key parameters and their values. The input is the normalized measurements ($\phi^*$) from the
spectral sensors. If we have $M$ sensors while each sensor has $N$ sub-bands of wavelengths, the input dimension will be $M \times N$. Next, we stack two 1D convolutional layers to extract the location’s informative spectrum features. The input channels of the layers change from 1 to 32 and 32 to 64 respectively, with a kernel size of 3 and stride step of 2. After every convolutional layer, the Relu activation [3] and batch normalization layer are employed. The Relu activation layer can improve the network’s non-linearity, which represents the physical environments better, while the batch normalization [14] makes the network training faster and more stable. Besides, to prevent over-fitting, we add a dropout layer between the two fully connected layers. The last fully connected layer generates the weights for all possible locations, which, in the next step, are used to calculate the predicted location coordinates $(x, y)$. In our model, the batch size is 32, the learning rate is $1e-5$, and the optimizer is Adam [19]. At last, the cross entropy loss function is applied to train the network.
5 EVALUATION

5.1 Goals, Metrics and Methodology

Our goal is to show that Spectral-Loc can achieve accurate indoor localization and improve the performance of conventional light intensity-based indoor localization. The metrics include localization error statistics such as median, 75th percentile, and 90th percentile errors. The evaluation methodology is described below.

5.1.1 Hardware Prototype. To measure light over the entire visible spectrum, we use AS7265x [35] as the hardware prototype of Spectral-Loc, which integrates three individual spectral sensors, AS72651-AS72653, for covering the three primary colors, GREEN, RED, and BLUE, respectively. Each individual sensor measures light from 6 different wavelengths within its primary color, thus measuring a total of 18 wavelengths or sub-bands within the spectrum ranging from 410 nm (UV) to 940 nm (IR). Each of the spectral sensor costs about $3.98 US dollars [27]. In each sub-band, the sensors can measure light intensity with precision down to 28.6 $nW/cm^2$ and accuracy of ±12%. The sensors’ normalized responsivity for different wavelengths is shown in Fig. 11. The whole sensor board has a compact size of 41mm × 37mm with 5mm thickness and 9.98 gram weight, which allows it to be easily carried by a person for experiments. We use an Arduino UNO to sample the spectral values from AS7265x at a rate of 1Hz and transmit them to a Raspberry Pi through USB cables. Each spectral sample, therefore, contains a vector of 18 elements representing light from the 18 sub-bands (wavelength range).

5.1.2 Experimental Environments. To evaluate the robustness of Spectral-Loc, we collected data from two different typical indoor environments: a small meeting room and a large open office space, which have different layouts, lighting, wall colors, and furniture.

The Meeting Room Environment is a 7.36m × 3.91m rectangular room with clear glass walls to the adjacent open office area. The room has two colored walls and a black carpet on the floor. In terms of lighting, the room is lit by two rows of Crompton T8 36W 840 fluorescent tube lights on the ceiling to produce diffused lights to the room. Furthermore, the light in the adjacent open office area affects the lighting conditions in the meeting room via the glass walls. Finally, we used a 1.4m high 420lm floor lamp with a switchable colour temperature between 2,000K (White) and 4,500K (Cool White), to provide further lighting control in the meeting room. Using April Tags [31] with identifying bar code, we marked 10 locations on the floor spreading in the room evenly. Two neighboring locations are approximately 1m apart. A photo of the meeting room is shown in Fig. 13.

Fig. 11. Spectral responsiveness and a photo of AS7265x, reproduced from [4, 35].
The **Office Environment** is a typical open office area with multiple rows of desks and cubicles. The office dimensions are 13.3m × 8.3m and in contrast to the meeting room, it is a much more complex indoor environment. There are a variety of furniture items including desks, light-blue partition walls, white plaster walls, metal cabinets, wooden bookshelves, and gray carpets. As highlighted in Fig. 1, the different materials have different reflectance profiles, resulting in spatially more diverse light spectral distribution. The entire office is illuminated by three rows of Crompton T8 36W 840 fluorescent tube lights and three circulars DULUX D 18 W/840 tubes on the ceiling to produce diffused ambient light. Apart from the light switches, we used two floor/desk lamps to further vary lighting conditions in our experiments. We marked a total of 51 locations in the corridors and between the rows of desks. A photo of the office space along with a location layout is shown in Fig. 12.

Fig. 12. The floor map (a), and the environment of the office evaluation area (b). The red points mark the locations, where we collect the lighting condition fingerprints. The distance between the two neighboring locations is approximately one meter.

Fig. 13. The layout of the meeting room.

5.1.3 **Sensor Placement.** To evaluate the number of sensors required by Spectral-Loc, we deployed a total of eight spectral sensors in different body locations such as the chest, back, left arm, left wrist, right arm, right wrist, front of the left calf, and back of the left calf (see Fig. 14). This allowed us to collect a comprehensive dataset for later analysis. As will be shown in Section 5.2.2, only 2 sensors would be adequate for Spectral-Loc to achieve accurate localization.
5.1.4 Data Collection. During each data collection session in a given room (i.e., either the meeting room or the office), a volunteer fitted with eight sensors moves from one marked location to the next while stopping at each location for approximately 30 seconds. Upon arriving at a given location, the volunteer first takes a picture of the April Tag, which helps assign the location labels to the collected samples. During data collection in the open office, we observed the occasional presence and movement of other people. To test the localization algorithm’s robustness over time, data collection sessions were repeated over multiple days. Table 1 summarizes the experimental settings and data collection statistics for both environments.

| Space            | Lighting Condition                                      | # of Days | # of Samples |
|------------------|---------------------------------------------------------|-----------|--------------|
| Office Area      | Default: turn on all lights                            | 5         | 9,698        |
|                  | Add two floor lamps                                    | 4         | 7,754        |
|                  | Turn off the middle row of ceiling lights              | 1         | 1,840        |
| Meeting Room     | Default: Turn on all lights in the room and adjacent open area | 5         | 1,411        |
|                  | Add one floor lamp                                     | 2         | 739          |

5.2 Results
We implemented the localization neural network model discussed in Section 4 in Pytorch [32] and evaluate its performance in this section.

5.2.1 Overall Localization Performance. We first benchmark spectral information against intensity using all eight sensors as shown in Fig. 14. Here, we collected data over five different days under the default lighting condition in both the office and meeting room (see Table 1 for the details). Then, we applied the leave-one-day-out testing, i.e., all data from 4 days are used for training, while the data from the remaining day is used for testing. We repeated this five times by selecting a different test day each time and report the average localization accuracy in Fig. 15 and three different percentiles in Table 2. Our results show that the light intensity approach (EHASS [40]) only achieves good localization accuracy for the small meeting room and it does not perform well in the large complex office environment even with eight sensors worn on different parts of the body. For example, while all percentile
errors in the meeting room are below 1 meter in the meeting room, the errors in the office environment are larger, with the 90th percentile error reaching 5 meters. In contrast, Spectral-Loc achieves sub-meter accuracy across both indoor environments even at the 90th percentile. This demonstrates that Spectral-Loc performs more robustly in large and complex indoor environments due to its greater capacity to exploit rich environmental reflectance to produce unique spectral fingerprints in individual locations.

We observe that Spectral-Loc achieves better performance in the small meeting room compared to the office. We believe that this is due to the greater number of possible locations in the office and so a greater probability of a location fingerprint being misclassified. We run additional experiments to validate our above observation and re-sample the number of locations in the office room from 50 to 5. Different sample strategies, for instance, selecting a small area randomly at the beginning and continuously adding more adjacent locations to expand the localization area, are used and their averaged results are presented in Fig. 16. For the small number of locations (less than 15), Spectral-Loc achieves comparable performance in the office to the meeting room. Increasing the number of locations leads to lower accuracy, however, Spectral-Loc performance stabilizes at around one-meter accuracy for 90th error distance.

![Fig. 15. Spectral vs. intensity under default lighting.](image)

![Fig. 16. The impact of the numbers of locations/fingerprint classes.](image)

Table 2. Median, 75th and 90th percentile errors for two rooms under default light conditions.

| Room Name       | Median Error (m) | 75th percentile Error (m) | 90th percentile Error (m) |
|-----------------|------------------|---------------------------|---------------------------|
|                 | Spectrum | Intensity | Spectrum | Intensity | Spectrum | Intensity |
| Office          | 0        | 0.66      | 0.05     | 2.00      | 0.98      | 5.07      |
| Meeting room    | 0.01     | 0.45      | 0.07     | 0.82      | 0.25      | 1.18      |

Proc. ACM Interact. Mob. Wearable Ubiquitous Technol., Vol. 7, No. 1, Article 37. Publication date: March 2023.
5.2.2 The Impact of the Numbers of Sensors. In this section, we investigate the impact of the number of body-worn sensors on Spectral-Loc’s localization performance. While maintaining the other factors, such as the lighting condition and the number of spectral sub-bands constant, we vary the number of sensors. Fig. 17 shows that the localization error reduces as we increase the number of sensors since more sensors provide richer lighting information. Nevertheless, the figure also shows that there is only a small difference in the 90th percentile error when using only two sensors (1.05 meters), compared to using all eight sensors (0.98 meters). The greatest benefit is obtained when adding the second sensor. To better visualize the impact of sensors at different orientations, we categorize sensor positions into four classes, based on their orientation: front, back, left, and right. We then draw the averaged 75th error distance distributions of all possible combinations of choosing two out of eight sensors. Fig. 18 shows that the two-direction combination, like, front and back, front and left, performed better than only using one direction, which is expected as the one direction will have lower information density.

5.2.3 The Impact of the Number of Wavelength Sub-bands. While AS7265x monitors 18 sub-bands, relying on fewer bands might have power and measurement time benefits. We, therefore, investigate the impact of the number of sub-bands on indoor localization performance. We analyzed two different policies to select the sub-bands. The first policy, which we call RGB-Restricted, always picks the same number of sub-bands from each of the three primary colors. For example, pick 1 sub-band from Red, 1 from Green, and 1 from Blue sub-sensing modules, which gives a total number of 3 sub-bands. Similarly, if we pick 2 from each primary color, then we have a total of 6 sub-bands and so on.

The second policy has no RGB restriction, i.e., it may have sub-bands selected from anywhere within the visible light spectrum. This policy allows us to select any number of sub-bands in total within the range of 1 to 18. However, unlike the RGB-Restricted policy, this policy may not cover all the primary colours.

For the RGB-Restricted, we evaluate all possible combinations and plot the average along with the 95% confidence level of the 90-percentile localization error in Fig. 19(a). For the second policy, the total number of combinations is too large, so we randomly pick up \( n \) sub-bands, where \( 1 \leq n < 18 \), from the 18 available sub-bands 250 times each and plot the average and 95% confidence bars of the 90-percentile localization error in Fig. 19(b). For \( n = 18 \), we just have one value, so no confidence level is plotted there.
We observe that the localization error decreases non-linearly as we add more channels but eventually the error plateaus. For the second policy without RGB restriction, the plateau point is reached at 8 sub-bands, adding more sub-bands does not improve localization any further. The RGB-restricted policy generally performs worse.

The analysis in Fig. 19(b) also shows that spectral-based localization outperforms intensity-based localization even when using a single wavelength. Specifically, the 90th-percentile of intensity-based localization error is 5.07m, while spectrum-based localization error is 4.5m with 95% confidence. This interesting observation can be explained as follows: measuring light intensity across a wide range of wavelengths effectively averages out the specific peaks at individual wavelengths, which reduces the discrimination capacity of the intensity-based method. Light intensity measurements may miss many subtle differences in the lighting environment, which could be otherwise picked up by an individual wavelength spectral sensor.

![Figure 19](image1.jpg)  
**Fig. 19.** Impact of the number of sensing wavelength sub-bands.

5.2.4 The impact of Lighting Interference - Adding Extra Lighting. In many indoor events, extra lights may be added temporarily to improve illumination in specific locations. For example, an attendee in a meeting room may turn on a floor lamp for improved visibility of an exhibit, while an office worker may turn on a desk lamp when trying to focus on a drawing. The temporary lighting can be a source of interference for the machine learning models used by Spectral-Loc which were trained with the default lighting condition. We investigated these scenarios by adding additional floor/desk lamps in the office and meeting rooms. Specifically, we placed a floor lamp in one corner of the meeting room and collected data on two different days during which we changed the lamp’s colour temperature between 2,000k and 4,500k. Similarly, we placed two lamps at two diagonally opposite desks in the office area and collected data for four days with 2 days in 2,000k and 2 days in 4,500k modes. We trained our localization network using the default non-interfering data and tested with data collected after adding the external lamps. The results are shown in Fig. 20.

From Fig. 20, we can see that the impact of interference was more pronounced in the meeting room compared to the office area. This can be explained by the fact that the meeting room is small and has fewer obstacles compared to the office area, which means the interference directly affected all the locations. In contrast, the lamps impacted only a relatively small area of the office environment. It is important to note, that even with the...
significant interference in the meeting room, Spectral-Loc was able to maintain sub-meter localization accuracy at 75th percentile.

5.2.5 The Impact of Lighting Interference - Lighting Failure. Lights in indoor environments can fail, which also introduces interference due to reduced light. We investigated the performance of Spectral-Loc under such conditions by turning off the middle-row lights in the office area, which causes a major disturbance to the default lighting. We then tested the localization system, which was trained with the default lighting condition, with data collected from the darker condition. Results are shown in Fig. 21. We observe a significant performance drop compared to the default lighting scenario, which was not surprising given the severity of the disruption. Nevertheless, Table 3 shows that Spectral-Loc can still maintain sub-meter (0.31m) median localization accuracy under the significant lighting failure, while intensity-based localization has a median error of 3.25m, a 10-fold increase in localization performance.

Table 3. Localization performance under lighting failure in the office.

| Lighting Condition                  | Median Error (m)  | 75th percentile Error (m) | 90th percentile Error (m) |
|-------------------------------------|-------------------|---------------------------|---------------------------|
|                                     | Spectral   | Intensity   | Spectral   | Intensity   | Spectral   | Intensity   |
| Default                             | 0.00       | 0.66        | 0.05       | 2.00        | 0.98       | 5.07        |
| Without Middle Row                  | 0.31       | 3.25        | 2.16       | 5.25        | 4.23       | 6.78        |

5.2.6 Performance with Sunlight. So far, we only considered night-time performance as all data were collected during night. In this section, we investigate the effectiveness of Spectral-Loc during daytime when sunlight enters the rooms through windows. The main challenge at daytime is the uncontrollable interference from the sunlight caused by dynamic weather conditions such as clouds. Keeping the same experiment settings in the office, we collected data during daytime in five different days with different weather conditions, including sunny, rainy and cloudy days shown in Fig. 24. Besides, all the curtains are rolled up in daytime. The intensity
values and the spectral distributions for these five days for a particular location are shown in Fig. 22 and Fig. 23, respectively. Specifically, the intensity lux fluctuates around 1,500 lux, which is close to the normal indoor sunlight intensity [39]. Also, the sunlight color changes at different times in a day [45]. To estimate the sunlight spectral changes, we position a spectral sensor on a window and collect the outside light’s spectrum data, as shown in Fig. 25. The graphs present the spectrum changes between 7:00 (sunrise) and 17:00 (sunset) over five days. The fingerprint data collection time is across morning, noon and afternoon. We observe that the sunlight’s spectrum does not change much outside of the sunrise and sunset periods, so our localization system achieves good performance most of the day. Overall, we can see that while the intensities for these five days vary considerably, the patterns of the spectral data are not really affected significantly. Given that Spectral-Loc exploits the patterns in the light spectrum for fingerprinting locations, we expect that Spectral-Loc can cope with sunlight better than localization techniques that exploit only the light intensity values. Indeed, Fig. 26, which shows results from leave-one-day-out evaluation, confirms that Spectral-Loc provides a more consistent performance across day and night compared to intensity-based localization.

5.2.7 The Impact of Surrounding Colors. In Section 3.4, we investigate that spectral information has more differentiable features in “complex” colorful environments than those in “simple” single color environments because the former will change the energy distribution of light sources and makes it unique in each location. Following the same experimental procedure in the meeting room and office discussed earlier, we collected data two times under both conditions (see Fig. 6). The data collected on the first day is used as the train set, and the second day’s data would be the test set. Table 4 shows the localization performance. Although Spectral-Loc produces good localization accuracy (i.e., less than 0.15 m median errors) under two conditions, the localization performance in “complex” colorful environment is significantly lower than that in “simple” environment; for example, 0.16 m vs 0.32 m and 0.34 m vs 0.70 m for 75th and 90th percentiles, respectively. This result verifies our hypothesis in Section 3.4 that the more variations of colors in a given environment, the more distinct the spectrum location signatures would be and therefore, the better spectrum-based fingerprint localization scheme, e.g., Spectral-Loc, would be.
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Fig. 22. Intensity values at a particular location across different days.

Fig. 23. Spectral distributions at the same location of Fig. 22 across different days.

Fig. 24. Weather conditions of daytime data.

Fig. 25. Spectral distributions of outer light at the same location over different days and times in a day. 7:00 and 17:00 are the sunrise and sunset time respectively.

Table 4. Localization performance under the controlled environment.

| Walls                  | Median Error (m) | 75\textsuperscript{th} %ile Error (m) | 90\textsuperscript{th} %ile Error (m) |
|------------------------|------------------|--------------------------------------|---------------------------------------|
| White walls (Simple)   | 0.15             | 0.32                                 | 0.70                                  |
| Colorful walls (Complex)| 0.11             | 0.16                                 | 0.34                                  |

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5.2.8 The Impact of Different Body Orientations. Our evaluation in Section 5.2.2 shows that the performance of Spectral-Loc with two sensors facing different directions is similar to that with more number of sensors. Therefore, we will one of such settings, i.e., the front and right combination as the example setting in this section. Although a user’s pose in the inference phase is different to that in the data collection phase, human motion inside buildings is typically constrained, for instance, along a corridor or through an intersection, which means the user may walk in four directions. Therefore, we propose to collect spectral fingerprints in four directions, i.e., South, West, East, and North, and use this data to train four different neural network models. Spectral-Loc can then exploit a digital compass [17] or inertial measurement unit (IMUs) [18] to estimate the walking direction of the person and select the right neural network model for inferring the locations. Fig. 27 shows that by selecting the “right” orientation model, Spectral-Loc produces similar localization performance in different walking directions. Furthermore, we also investigate the impact of the arbitrary rotation angles on the performance of Spectral-Loc, by conducting quantitative experiments in the office room environment. First, we select three random locations in
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We deploy a spectral sensor at each location and point it towards a random angle. We then rotate the sensor by 0 to 40 degrees in 10-degree steps. For each step, we measure the Euclidean distance between the spectral distributions corresponding to the initial and rotated angles. The averaged differences and standard deviations are shown in Fig. 28 (b), which shows that the spectral distributions change with an increasing rotation angle, unsurprisingly. In addition to the quantitative study discussed above, we also evaluate

(a) Quantitive rotation experiment setups.  
(b) The spectrum changes against rotation angles.

Fig. 28. The controlled rotations.

the impact of the rotation angle on the localization performance of Spectral-Loc. Here, we use the 0-degree setup in the training phase and the rotated 10 and 20 degree configurations in the inference/testing phase. Fig. 29 shows that the performance Spectral-Loc degrades as the rotation angle increases, however, the 75th error remains within 1.4 meters for 20 degree rotation. Therefore, for the arbitrary user orientation, we propose to collect the spectral fingerprints from a fixed number of orientations at each location, while the number is selected based on the application localization accuracy requirements. We then train a neural network model for each orientation during the training phase, and select the closest orientation network model based on the walking direction estimation from IMU or digital compass measurements in the inference phase.

5.2.9 The Impact of Other Environmental Factors. In the previous sections, we only investigated the environmental impact of light condition changes, which include light interference and sunlight. As our system is based on ambient light, the other environmental factors, for example, temperature and humidity, will not affect the proposed system significantly. To verify this, we perform a controlled experiment in a room, where we keep all conditions fixed but alter the temperature and humidity with a heater. To monitor the temperature and humidity changes, we deploy a DHT11 [2] sensor near the spectral sensor. A Heller 2000 portable heater [12] is placed under the table and produces hot air wind to change the room’s temperature and humidity. Fig. 30 shows that the temperature and humidity have negligible impact on the spectral sensor’s readings.

6 LIMITATION AND FUTURE WORK

In this section, we discuss and reflect on some of the limitations and future works of the current study.

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Fig. 29. Localization performance comparisons of different rotation angles.

Fig. 30. The controlled room with different temperatures and humidity. Every colorful line in (b) and (c) represents one sub-band reading of spectral sensors.

**Impact of human interference.** Humans can block lights and hence interfere with light-based localization. During the data collection in the office area, we observed the occasional movement of people in the area. We can therefore conclude that the presented results are robust against mild human interference, which can be expected in meeting rooms, open office areas, residential spaces, and so on. Further study would be required to understand the full impact of human interference in crowded indoor environments, such as shopping malls or underground train stations.

**Localization for walking users.** In this work, we considered localizing users standing at a particular location, hence using light spectral data gathered from a fixed location for fingerprinting. Recent works with light intensity-based localization [49] have demonstrated that localization accuracy can be significantly improved by considering a vector of multiple light intensity values collected from a series of locations in the user’s walk trace. We believe that the reported localization accuracy values for Spectral-Loc could also be improved further for walking users with such trace data, but such studies would be orthogonal to the current study.
Indoor robot navigation. Based on the results shown in Section 5, light spectral measurements are location informative that have no need for modifications of light sources. In addition to assisting human localization, light spectral-based fingerprints may be used to improve robot navigation. Here, multiple sensors facing different directions may be embedded in the robots to enrich the spectrum information and improve its localization performance. In the future, we will study and apply Spectral-Loc in robot navigation systems to help with monitoring, cleaning, and delivering services.

Sensed spectrum. We used AS7265x whose sensing is limited within 410nm-940nm, which we believe was adequate to capture the lighting and the reflections within our experimental indoor spaces. For more diverse indoor spaces comprising a wider range of lights and materials, it may be worth sensing a wider spectrum, such as using AS7341 [5] which can sense from 350nm to 1,000nm.

Energy consumption. Spectral sensing would have higher energy consumption compared to basic intensity sensing due to sampling and signal processing from multiple light wavelength sub-bands. However, the analysis presented in this paper has shown that the impact of the number of sub-bands on localization accuracy is non-linear, i.e., the localization error can be reduced significantly by using a few sub-bands but adding more sub-bands thereafter provides only marginal improvements. This discovery indicates that the energy consumption of the proposed light spectrum-based localization can be reduced significantly by using sensors that measure a smaller number of sub-bands. For example, AS7265x measures 18 sub-bands and requires a supply voltage of 2.7-3.6V, whereas AS7341 measures 8 sub-bands using only 1.8V.

7 RELATED WORK
Over the past decades, researchers focused on localization techniques based on many different types of radios, for instance, WiFi [1, 7], Bluetooth [6, 50], Lo-Ra [22], ZigBee [6, 30, 37], and Ultra-Wideband (UWB) [11, 33]. These wireless-based localization methods can achieve localization accuracy from cm level to m level depending on different systems. However, the wireless signal-based approaches are susceptible to interference from other wireless communications in the environment.

As light is readily available and densely deployed in most indoor spaces, there has been a recent interest in utilizing visible light for indoor localization. Light-based localization systems can be broadly categorized as modulated, where lighting infrastructure is modified, and unmodulated, which enables localization using only the existing ambient light.

Modulated Light. Luxapose [20] modified LED with pulse width modulation. Spatial beams have been identified with the unique timed sequence of light signals in Spinlight [46]. For light polarization, Celli [44] projects interference-free polarized light beams and PIXEL [47] using the liquid crystal to modulate the polarized light. SmartLight [23] uses the light splitting property of a convex lens. EyeLight [29] uses reflection property of light for localisation. Those different types of techniques have been explored to modulate the light source, which can enhance the distance relationship between the users (receivers) and light sources (transmitters). For example, FogLight [25] used the off-the-shelf digital projector combined with a light sensor. It projected the grey-coded binary pattern using the alternating property of the Digital Light Processing, then decoded and transformed this binary pattern and sent the position via their WiFi module. By leveraging white and black to represent 1 and 0 inside the projection area, the pixel can be represented as a sequence of binary digits. They can achieve a high accuracy result in localization with the light projection, which achieves 0.3 cm for 90th percentile distance errors. Apart from using intensity information, [38] augmented indoor inertial tracking by reusing existing indoor luminaries to project a static light polarization pattern in the space. It uses polarizers and birefringent films to create an imperceptible grid pattern of light polarization. As the polarized light is imperceptible to human eyes, a simple color sensor is used to decode the polarized colorful pattern. However, the spectrum changes are caused
by the modulated light source. How to utilize spectral information with unmodulated ambient light has not been investigated yet.

**Unmodulated Light.** For the unmodulated scenarios, the critical problem is finding location-related features. One way is regarding the light source as landmarks and acquiring its discriminative features [13, 28, 48]. LiTell [48] captures the unique frequency of fluorescent lights through cameras to match the known location. The other way is extracting information from light. Intensity is one of the primary measurements of light, while it is a scalar value that lacks unique identification of locations. To address this problem, NaviLight [49] observed intensity changes with a specific walking path. They used light intensity as a fingerprint similar to people using the Received Signal Strength Indicator (RSSI) of WiFi as a fingerprint. However, light intensity is ambiguous over the air. It is not enough to only use it to do fine-grained localization. Hence, NaviLight firstly uses a k-nearest neighbours classifier to do a coarse-grained localization. After that, it collected IMU data from users' movement, divided the fingerprint vector into small chunks, and then mapped it in the light intensity floor map for fine-grained localization. Combining other sensors can be another way to help identify locations, for instance, using magnetic sensors [42, 43]. They used the magnetic and intensity data to create bimodal images. These are the main two ways to extract more location-related information. Generally, compared with the modulated light source, the cost of the non-modulated light source method is relatively smaller, but the processing of the received light signal and the algorithm of localization will be more complex and computationally intensive.

With the light-based localization method, the challenge such as interference from blocking between users and light sources, interference from the ambient light sources, and not working in light-off mode happened in most systems. Some studies try to address these issues. For example, EyeLight [29] addressed the Line of Sight problem by leveraging shadows. However, its price for this is a reduction in localization accuracy. These tasks are still to be addressed in future works.

**Spectral sensors.** Spectral sensors can be divided into two categories: RGB color sensors and multiple sub-band sensors. The RGB sensors use interference filters to measure the absolute values of three color sub-bands. After calibration, the sensitivity for this kind of sensor is similar to human eyes. The other type of spectral sensors is multi-band spectral sensors, such as AS7265x [35] we used, which measure the radiant power for multiple sub-bands. With the help of spectral sensors, we can tell whether the orange light is mixed with red and yellow light or pure orange light. They have been used in smartphones, for instance, Xiaomi [10], Huawei [9], where the spectral sensor can acquire accurate white-balancing to improve the rendition of color in photography. Besides, spectral sensors can be applied in video equipment and virtual reality devices. Through the spectral readings, the light sources can be analyzed to differentiate the light source type, for instance, LED, solar, etc. In this way, according to the spectrum, accurate color compensation for different light sources can be proposed to improve the video rendering effect, which makes the devices robust to different light conditions. Besides image rendering, spectral sensors have been recently used to detect radiation [21] and airport lighting types for automated lighting maintenance [36]. To the best of our knowledge, the use of spectral sensors for indoor localization is yet to be reported in the open literature.

### 8 CONCLUSION

We have studied, for the first time, the potential for indoor localization using the light spectrum information extracted from the ambient lights. Our study has confirmed that light spectrum information that can be measured using low-cost and low-power COTS sensors is capable of fingerprinting typical indoor locations much more accurately than that of the light intensity information. We have developed signal processing and machine learning required to exploit light spectral information for indoor localization. In our experiments with a meeting room as well as a large open office space, we were able to realize sub-meter median accuracy for the proposed light-spectral-information-based localization system using only a single sensor on the user body. These encouraging
results combined with the recent proliferation of spectral sensors in commodity mobile devices are expected to open up new avenues for precise indoor localization using only the existing lighting infrastructure.

ACKNOWLEDGMENTS
The authors would like to thank the reviewers and the helps from Yuezhong Wu and Wei Song, for their insightful discussions. This work was partly supported by the Australian Research Council Discovery Project DP210100904, UNSW Scientia PhD Scholarship Scheme and CSIRO Data61 PhD Scholarship Program.

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