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Exploiting Color Sensors to Provide Optimal Lighting and Anonymous Tracking in Stores

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***Abstract*—To compete with online shopping, retailers are constantly looking for ways to improve the display of their products and to track customers to obtain shopping patterns. We propose a general framework that exploits simple color sensors on ceilings to tackle the above-mentioned challenges. Our first contribution is a tunable lighting system that estimates accurately the *true color* of a product, and then, adjusts automatically the type of lighting to increase the product's appeal. Based on this accurate estimation of color, our second contribution is a system to track people anonymously. Relying solely on the reflections coming from people's clothes, hair and skin, we use color sensors to generate unique *optical signatures* for individuals. Our evaluation shows that, in spite of the limited information provided by color sensors, the optical signatures are precise enough to differentiate people with very similar appearance except for some minor differences in their clothing.**

***Index Terms*—Visible light, Indoor Tracking, Tunable lighting.**

I. Introduction

Motivation. There is a strong correlation between the success of retail stores and their lighting design [1]. In particular, the *color temperature* of light fixtures can positively influence the customer's perception of a product, and thus, increase overall sales [2]. This occurs because the object's color is heavily dependent on the spectrum of the light source. For example, warm light has a stronger yellow component, thus, given that an object 'simply' reflects back what it receives, the object will look more yellowish. Stores regularly exploit these effects to market their products, for instance, it is well known that bread looks tastier under warm light and fish looks fresher under cold light.

Presently, however, retailers can only adjust the color temperature manually. This problem could be solved trivially using a camera to detect the color of the product, but in some cases such a method would not be allowed due to privacy concerns. A study by Philips Lighting (now Signify) found that 60% of shopping decisions are made in the fitting room for fashion stores [3]. Retailers want their customers to see themselves in favorable lighting conditions, but using cameras in fitting rooms to achieve such a goal would be clearly unacceptable. There is a demand for an *automatic tunable lighting system* that preserves privacy.

Another important need for retailers is to track the whereabouts of customers to data-mine shopping behaviour. Some camera systems can provide accurate and anonymous tracking indoors, but we propose an alternative that is privacy preserving from inception. Even if a color sensor is hacked it would not be possible to identify an individual. Color sensors are less complex and consume less energy than cameras, but they have not been considered for tracking due to their coarse granularity. Figure 1 shows two images that can be uniquely identified with a camera (left), but not by a color sensor because all incoming light is averaged into a *single pixel* (right).

(a) Camera's view (b) Color sensor's view

Fig. 1: Color information obtained by cameras vs color sensors

Implementing both applications based on color sensors (tunable light and people tracking) would allow cost savings for the retailers, as they would only need to install one sensor system – simple and inexpensive color sensors in this case.

Challenges. For the purpose of our applications, the unique properties of color sensors lead to three main challenges.

(1) Achieving long ranges. Current applications for color sensors have a limited range: a few centimeters. In our scenarios, the distance between the color sensor and the object is expected to be beyond 1 m, as the sensor will be on a ceiling. The longer the distance, the lower the intensity of the reflected light from the object, resulting in a lower detection accuracy.

(2) Variable Lighting Conditions. The type of surrounding light changes the *object's true color*[1]. These inconsistencies in lighting conditions can be intended (to promote a product) as well as unintended. We need to analyze the effect of external light sources on the object's true color.

(3) Unique Object Identification. This challenge is only related to the indoor tracking application. A single-pixel provides limited information. Thus, it is not-trivial to distinguish two people passing under a sensor with similar external colors.

Part of this work is currently going through patent applications in the EU. The company, Tridonic GmbH & Co KG, has authorized the publication of the study.

[1]An ***object's true color*** is defined as the object's color under pure white light, i.e. light that contains all the colors of the visible spectrum equally

How unique can optical signatures be? And how accurate can indoor tracking be with such limited information?

Contributions. Our work addresses the above challenges and proposes two novel applications based on color sensors:

An automatic tunable lighting system (Lux-Tune). We show that, when color sensors are utilized directly out-of-the-box in our envisioned scenarios, the estimation can be highly erroneous. For example, blue colors are detected as gray or yellow. Such glaring errors can lead to changes in lighting conditions that would make products look worse not better. We propose a simple calibration method to overcome issues related to long ranges and variable lighting conditions. Our method follows the guidelines of the CIEDE2000 standard. Although similar correction methods have been used in other sensor technologies (e.g., digital cameras), to the authors' best knowledge such methods have not been applied on simple color sensors.

An anonymous tracking system (Lux-Track). Obtaining accurate color measurements (contribution 1) allows us to show that color sensors can provide distinctive optical signatures for people walking around an area. To map these optical signatures to the correct person we use Dynamic Time Warping (DTW) and correlation functions. Our evaluation shows that, in spite of the limited information conveyed by reflections, our system can distinguish people with very similar external features.

II. Lux-Tune

In this section, we describe the methods used to tackle the first two challenges presented in Section I. The aim is to have a sensor on a ceiling capable of detecting the true color of an object underneath and adjust the temperature of the light fixture accordingly to make the product more appealing. Our system allows setting any light color temperature according to some predefined rules. We adopt conclusions of studies about customers' favorable lighting conditions [2].

A. Selecting the right type of sensor

There are three main types of color sensors: RGB, True Color and Multispectral. The latter provides high accuracy but at a high cost (hundreds of dollars), thus, we discard them. The first two are inexpensive because they use simple photodiodes and optical filters. The key difference is that true color sensors use interference filters to emulate the human perception of light (human eyes do not have the same sensitivity to all colors, some colors stand out more than others).

Due to their low-cost and ability to capture people's perception, our system uses true color sensors. To select the best option, we benchmark the performance of three sensors (MTCS-INT-AB4, MTCS-C3 and AS7221) in an office space with a controlled light source. This initial benchmark considers a sensor-object distance of 30 cm and tests different colors (red, green, blue, white) under various light intensities and color temperatures. We found that the AS7221 performs the worst, measuring white as light blue. To differentiate the performance of the other two sensors we use the framework proposed in [4], which relies on the CIEDE2000 standard and states that a color difference of less than 3.5 is not easily detected by people. The MTCS-INT-AB4 provides always color differences below 3.5, while the MTCS-C3 has differences between 5.5 and 6.5 for the blue channel, and between 2 and 4 for the green channel. Thus, we use the MTCS-INT-AB4 in our system.

An important parameter of the selected sensor is the integration time, which is the time needed by the sensor to gather enough incoming light to provide an accurate measurement. The lower the light intensity reaching the sensor, the longer the integration time required, and thus, the lower the sampling rate. The values of the integration time are application-dependant and they are determined in Section V.

B. Long Range & White Balancing

Let us assume that the output values for each color channel (R,G,B) are in the range $[0{-}N]$. If a white surface is measured, all three channels should have a value of N. But if the distance between the sensor and the objects increases, the received values decrease because less light reaches the sensor. As a consequence, the estimated color will be a darker version of the object's true color due to lower sensor values.

White balancing is a simple solution that can be applied for this problem [5]. Letting $X(i)$ be the (erroneous) value measured at each channel i and $Ref(i)$ be the maximum value N that a channel can take, $\gamma(i)$ in Equation (1) is a scaling factor that normalizes the erroneous measurements to provide the correct values $W(i)$ using Equation (2).

$$\gamma(i) = Ref(i)/X(i) \tag{1}$$

$$W(i) = X(i) * \gamma(i) \tag{2}$$

C. Color Bias & Calibration Matrices

White balancing is not the only problem faced by color sensors, there is also a high level of color bias. In principle, red, green or blue objects should result in RGB values of (255,0,0), (0,255,0) and (0,0,255), respectively. In practice, however, the received values can be very noisy, for example, a pure red surface can have (245,50,0) values instead of (255,0,0). This occurs because sensors increase (or decrease) the strength of some color channels due to *cross talk* (leakage of light rays among channels) and *varying spectral responses* (different sensitivities for different colors).

These effects cannot be eliminated with a linear normalization, as done with white balancing, we require calibration matrices [5]. A *calibration matrix* K that satisfies Equation (3) can be used to obtain the correct values C, based on the matrix W obtained after white balancing (all matrices are 3×3). Such calibration matrix can be expressed as a function of ground-truth matrices T and sample matrices W as shown in Equation (4).

$$C = K \cdot W \tag{3}$$

$$K = (T \cdot W^T) \cdot (W \cdot W^T)^{-1} \tag{4}$$

To quickly evaluate the effectiveness of our correction algorithm, we use surfaces with different colors as shown in Figure 2a. The distance between the sensor and the surface of interest is 70 cm. After applying the white balancing method, the estimated colors are shown in Figure 2b. We can observe that, except for yellow, no color is measured accurately, with blue being particular off target. When we apply the calibration matrix, on top of white balancing, the estimations capture accurately the true object's color, c.f. Figure 2c.

(a) ground truth

(b) White balancing

(c) White Balancing + Matrix Calibration

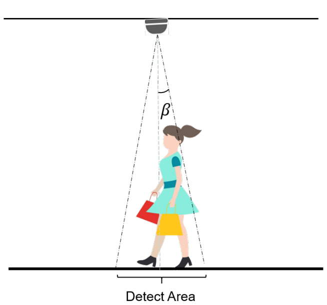
Fig. 2: Color detection results for Lux-Tune

III. Lux-Track

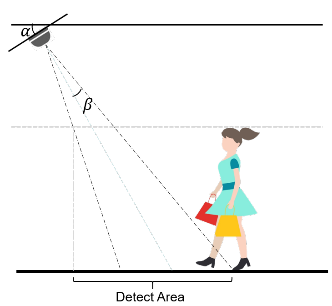
Lux-Tune (Section II) requires a tunable light and color sensors, but Lux-Track only requires color sensors. Within its field of view (FOV), each sensor detects the light reflected by people moving underneath with any arbitrary physical appearance (skin color, hair color, clothes, etc.). When a person enters the system, a new optical signature is recorded. Later on, as the person passes underneath the other sensors, the optical signatures are mapped to the first signature, providing in this manner tracking information. As mentioned in Section I, the main challenge for this application is how to assign and track optical signatures.

A. Optical Signatures

In the Lux-Tune system, sensors face vertically the object of interest. That setup minimizes the distance between the sensor and the object, improving the color detection accuracy. For the tracking system, however, such a setup would only detect the person's top-view (hair & shoulders), as shown in Figure 3a, limiting the ability to create unique signatures. Installing the sensor at an angle allows a more complete coverage of physical appearance. For example, in Figure 3b the color sensor will record a signature that goes from black (shoes), to yellow (skirt), to light blue (blouse) to brown (hair).



(a) Sensor aimed at ground



(b) Sensor tilted at an angle α

Fig. 3: Sensor Setup

It is important to highlight the role played by the floor because its color will 'mix' into the detected optical signature. The floor can have any color pattern but we assume it to be consistent across the area of interest. The floor's color also provides a baseline to determine when to start and stop the collection of optical signatures, deviations from the baseline trigger the start of the data collection process and this process stops when the sensed color returns to the baseline.

B. Mapping optical signatures

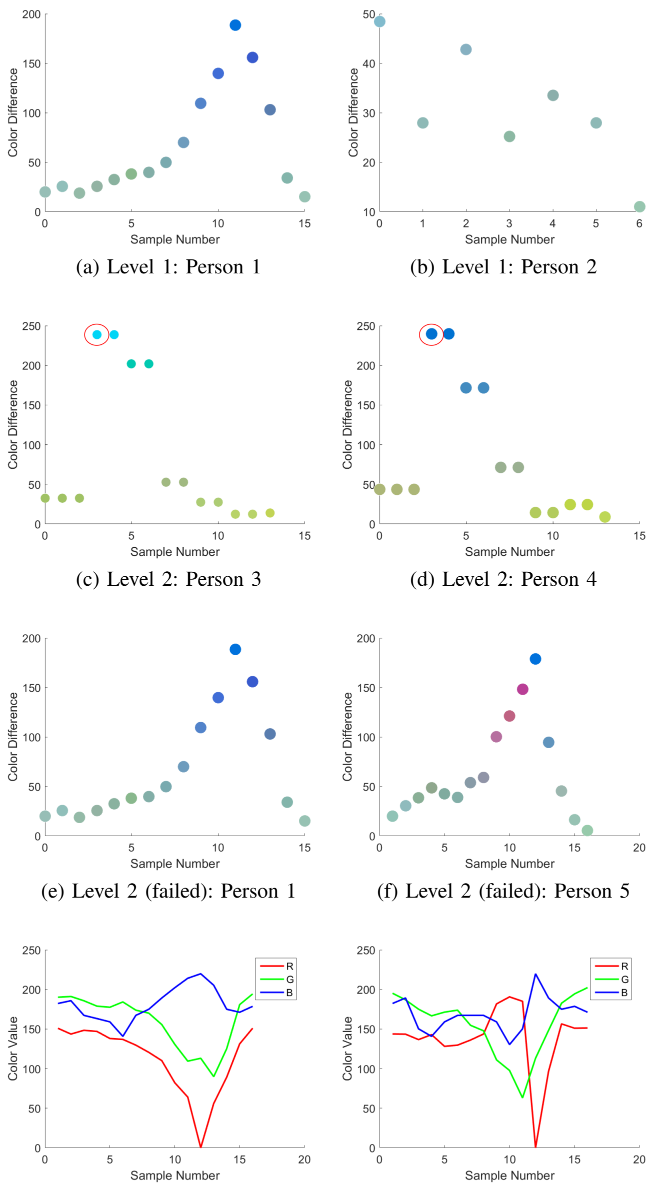
Once an optical signature is gathered we use a 3-level approach to identify if it corresponds to a person already present in the area or if it is a new customer. To highlight the characteristics of these three levels we use five people with physical appearances ranging from very different to very similar. Also, it is important to mention that our method requires various thresholds, the values for those thresholds are discussed in Section V.

Level 1. Color Differences. The first step to detect if a new person has entered an area is to check the color difference with respect to the background. Figure 4a and Figure 4b show the color values of two different people. In these plots, the color of each circle represents the combined color information reaching the sensor. The x-axis depicts the sample number and the y-axis the color difference w.r.t. the floor. For the level-1 comparison, if the average color difference between two optical signatures is above a predefined threshold, the person is deemed to be a different one (Person 2 in this case, Figure 4b). Otherwise, the method goes to the second comparison level.

Level 2. Peak Value Comparison. Two people with different physical appearances might be identified as the same person in the level-1 comparison. For example, Figure 4c and Figure 4d show two level-1 signatures that look similar even though the color values of some points are different, such as those at the peak (circled in red). For these situations, the second level compares the peaks in the level-1 signature. The peak represents the moment when the difference between the background and the person is the highest, that is, when the sensor has the best coverage of the person. If the difference is above a given threshold, the person is deemed to be a different one, else the method goes to the third comparison level.

Level 3. Individual Channel Differences. In some cases, level-2 signatures will not be able to differentiate people. For example, if a person wears a red sweater and a blue hat while another person wears a blue jacket (both wear similar pants), the system outputs the signatures shown in Figure 4e and Figure 4f. These two persons have similar peak values because at the moment of greatest coverage, the blue hat overpowers the red sweater because it is closer to the sensor, providing a similar peak value to the blue jacket. To resolve these situations, a level-3 comparison is used to analyze each color channel independently. The color signals are decomposed into triplets. For example, Figure 4g and Figure 4h depict the signature triplets for Figure 4e and Figure 4f, respectively.

Comparing the signature triplets, however, is not straightforward. In a real setting, there are three phenomena that can lead to the creation of multiple signatures for the same person, creating in effect multiple people out of single person and making it impossible to track users.



(a) Level 1: Person 1
(b) Level 1: Person 2
(c) Level 2: Person 3
(d) Level 2: Person 4
(e) Level 2 (failed): Person 1
(f) Level 2 (failed): Person 5
(g) Level 3: Person 1
(h) Level 3: Person 5

Fig. 4: *Level 1* (a, b): color difference. *Level 2* (c, d): peak color difference. *Level 2 fails* (e, f): two persons have the same level-2 signature. *Level-3* (g, h): individual channels.

[**P1**] *Different walking directions*. The color pattern depends on the movement direction. For example, a person that passes a sensor from left to right will have a different optical signature when she passes it from right to left.

[**P2**] *Fluctuations in light intensity*. Lighting is not even. The intensity is higher directly below a lamp and decays as one moves away, which means that, for the same person, the detected color is a lighter or darker version of the true color.

[**P3**] *Different walking speeds*. The same person may move at different speeds when walking under different sensors, changing the length and shape of the recorded color sequences.

To solve **P1**, we compare the flipped counterparts of each signature as well, allowing us to detect a person independently of the direction of movement. To solve **P2** and **P3**, we combine two popular methods used to measure signal similarity: the correlation coefficient and dynamic time warping (DTW). The correlation coefficient ρ, Equation (5), is the most rigorous way to measure similarity and copes well with changes in amplitude because it normalizes the signals with respect to the mean and standard deviation (solves **P2**), but the signals must have the same length (**P3** remains an issue).

$$\rho_{X,Y} = \frac{E[(X - \mu_X)(Y - \mu_Y)]}{\sigma_X \sigma_Y} \tag{5}$$

DTW has the opposite trade-off. DTW relaxes the notion of similarity by focusing mainly on the signals' shape. DTW can compare signals with different length (solves **P3**), but it is not well suited to deal with different amplitudes (**P2** remains an issue). Normalization is a simple technique to homogenize the amplitude of signals, but in our case, normalizing the signal would prevent the possibility of distinguishing colors of the same tint, for example, blue (0,0,255) would be the same as dark blue (0,0,100).

To compare signals with different amplitudes (**P2**) and lengths (**P3**), we combine the correlation coefficient with DTW. There are various methods to combine DTW with other similarity metrics. Given two signals $S1$ and $S2$ of different length, the simplest way to combine correlation coefficients and DTW is to first use DTW to align the signals, and then, calculate the correlation coefficient between these two aligned signals. For example, letting $S1 = [1, 1, 3, 5, 5, 2, 2]$ and $S2 = [1, 3, 5, 2]$, aligning them with DTW would lead to $S2' = [1, 1, 3, 5, 5, 2, 2]$, and the correlation coefficient of $S1$ and $S2'$ would be 1. Although this method is sufficient to solve the problem, we modify the calculation of the correlation coefficient to integrate it within the alignment process itself. Due to space limitations, we omit the steps used to derive our method and present only the final result in Equation (6), where $E1 = \sum S1^2(n)$ and $E2 = \sum S2^2(n)$.

$$\rho = \frac{(\sum[S1(n) * S2(n)])^2}{E1 * E2} \tag{6}$$

We can observe from Equation (6) that the calculation of ρ does not involve deriving the mean or standard deviation. It only requires calculating the energy of the signals ($E1 \& E2$) and the sum of the products of the aligned points ($(\sum[S1(n) * S2(n)])^2$). These three components can be calculated during the alignment process of DTW. If we consider again signals $S1$ and $S2$, the adjacency matrix D according to DTW is shown in Figure 5. Following the shortest path in D, starting from the top left, at every alignment point ($S1(i)$, $S2(j)$), we calculate $E1 = E1 + S1(i)^2$, $E2 = E2 + S2(j)^2$ and $B = B + S1(i) * S2(j)$, leading to $E1 = E2 = B = 65$, which in turn leads to $\rho = \frac{B^2}{E1 * E2} = 1$ (same value as if we would calculate the DTW alignment first and then ρ)

Multi-level comparison. Overall, our method works according to the flowchart in Figure 6. New data first goes through the level-1 comparison. If the correlation coefficient ρ is greater

S2 \ S1	1	1	3	5	5	2
1	0	0	2	4	4	1
3	2	2	0	2	2	1
5	4	4	2	0	0	3
2	1	1	1	4	4	0

Fig. 5: Adjacency matrix D

than a predefined threshold T, the data undergoes a level-2 peak comparison. If the color difference of the peaks is smaller than a predefined threshold, a level-3 comparison is performed on all three color channels (R, G, B). Level-3 signatures are deemed to be the same only if all three channels are similar: $(\rho_R > T_R) \wedge (\rho_G > T_G) \wedge (\rho_B > T_B)$. If no match is found, the signature is stored as a new person (entry) in the database.

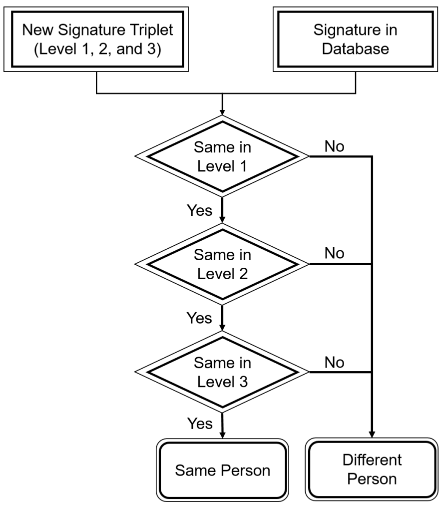


Fig. 6: Signature Triplet Comparison Flowchart

IV. Implementation

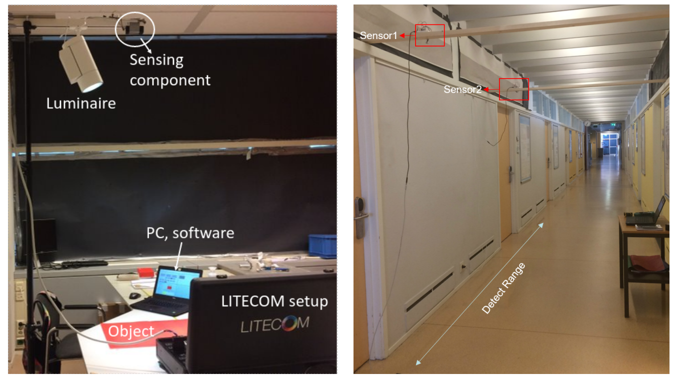
Hardware Platform. Our system has two main components: illumination and sensing. The sensing component is required for both applications, while the illumination component is required only for the Lux-Tune application. The Lux-Track application does not require any specialized illumination unit, it can work with any artificial lighting already installed in a building. Each component is explained next.

The *sensing component* consists of a color sensor, a microcontroller (MCU), and a wireless communication module. The MCU collects the data from the sensor and calibrates it as explained in Section II. The wireless module sends data to a remote user interface. The *illumination component* uses an ARCOS 3 tunable white LED from Zumtobel [6] and the color temperature is controlled by a proprietary LITECOM controller. Table I lists the hardware used in Lux-Tune and Lux-Track, and the respective deployments are shown in Figure 7: a standard office space for Lux-Tune and an aisle in our building for Lux-Track.

Software Platform. The Lux-Tune system has two phases: calibration and operation. Both phases are controlled and monitored with the GUI shown in Figure 8a. The calibration phase requires placing four different colored surfaces under the sensor (red, green, blue, white) at nine different temperatures[2] between 3000K and 6000K. Each <surface, temperature> tuple can be selected in the top left quadrant of the GUI. The system then obtains the corresponding calibration matrix (bottom-right quadrant). After the calibration is complete for all 36 tuples, the user can switch the system to the operational phase (top-right quadrant). In this phase, the system first pulls the calibration matrix for the current light temperature, then uses that matrix to detect the object's true color, and finally, adjusts automatically the temperature of the tunable light to make the product more appealing (bottom-left quadrant).

TABLE I: Hardware List

Color sensor (both)	MTCS-INT-AB4 (true color)
Microcontroller (both)	ESP32 (contains WIFI module)
Luminaire (Lux-Tune)	ARCOS 3 tunable white
Light controller (Lux-Tune)	LITECOM device
Luminaire (Lux-Track)	Standard lamps in the aisle



(a) Lux-Tune (b) Lux-Track

Fig. 7: Hardware deployment

In the Lux-Track system, the sensors are deployed on the ceiling and they send the detected color values to a central server to perform the 3-level comparison presented in Figure 6. The GUI in Figure 8b shows a person that has being identified while passing one of the sensors.

Videos of evaluation. We have posted two anonymous videos showing brief demos with their respective GUIs.

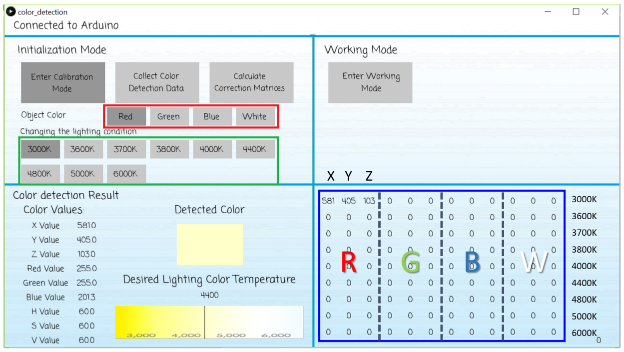
- Lux-Tune: https://youtu.be/-02796wmqmE
- Lux-Track: https://youtu.be/2SHfcyk0cnM

V. Evaluation

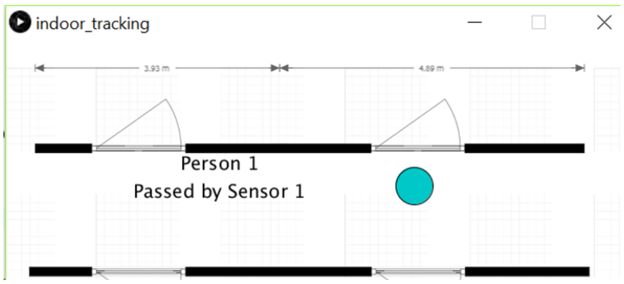
The *Lux-Tune* system is evaluated in an office space that already has four light bulbs. These bulbs are used to analyze the effect of interference. The color temperature of those light bulbs is 3500K, and the temperature of the tunable luminaire ranges from 2700 to 6500K. The distance between the sensor and objects is adjustable, but the maximum distance we test is 1.7 m. For that distance, the sensors' integration time is set to 128 ms to obtain accurate measurements.

The *Lux-Track* system is evaluated on a corridor with two sensors placed at 2.2 m. The color temperature of the lights is 4000K, thus, we use the calibration matrices of that

[2] Nine temperature modes are sufficient to cover most product colors [7].



(a) Lux-Tune



(b) Lux-Track

Fig. 8: The GUI of our applications

temperature to obtain the optical signatures. As explained in Section III, the sensor must be tilted at an angle to provide a better coverage. But the tilted angle increases the distance to the floor and people, which in turn reduces the received light intensity. To optimize the coverage-intensity trade-off, we set the tilted angle α to 30°. Considering the lights present in the corridor, the sensors' height and the tilted angle, the light intensity arriving to the sensor (via reflections) is lower than 26 Lux, which requires an integration time of 512 ms to obtain accurate results. Compared to Lux-Tune, this integration time reduces Lux-Track's sampling rate from 8 Hz to 2 Hz.

A. *Lux-Tune performance*

Considering the scenarios seen in stores, we identify three key factors that need to be evaluated: the object's material, the distance between the sensor and the object, and the interference caused by ambient light. Our metric for accuracy is the difference between the object's true color and the detected color as dictated by the CIEDE2000 standard [8] and its corresponding formula [9]. The experiments are performed after the mandatory calibration step explained in Section II.

Effect of material. Lux-Tune could be used for clothing (fitting rooms), fruit (supermarkets) or other products, and the reflective properties of objects can vary significantly. To cover different ends of the reflective spectrum, we evaluate paper and cotton, since the former has a higher reflectivity than the latter. Both objects are placed 71 cm from the sensor. The color detection accuracy of red, green, and blue objects for both materials, with varying light intensity and color temperatures, is shown in Figure 9. The dotted line at $y = 3.5$ represents the value above which the difference is large enough to be noticed by people. For the varying light intensity (top plots), the temperature was fixed at 6500K, and for the varying temperature (bottom plots), the intensity was fixed at 100%.

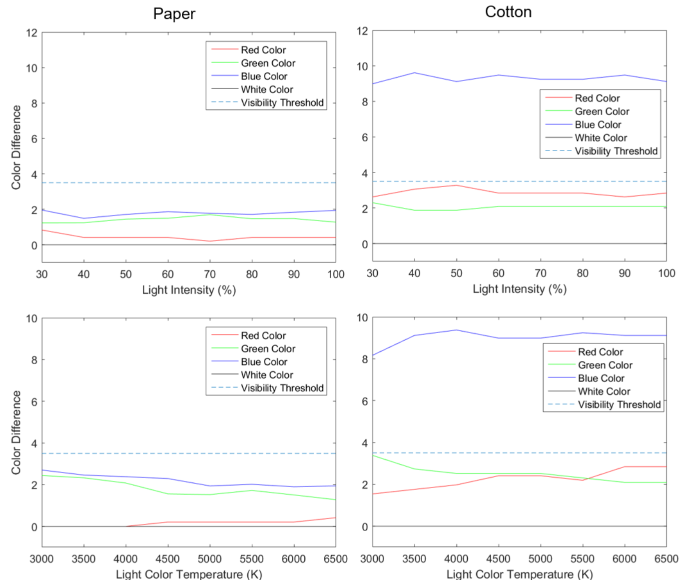


Fig. 9: Detection Accuracy of Paper and Cotton

We can observe that the difference is not noticeable for any <color, intensity, temperature> tuple, except for blue cotton (due its lower reflectivity). However, as long as the detected color is a tint of the true color, the correct temperature will be picked to illuminate the object, which will increase its appeal.

Effect of distance. In some cases the object may be close to the sensor (meat section in supermarkets), and in others it may be further away (fitting rooms). We vary the distance between the sensor and object from 0.71 to 1.5 m, which decreases the light intensity arriving at the sensor from 171 to 42 Lux.

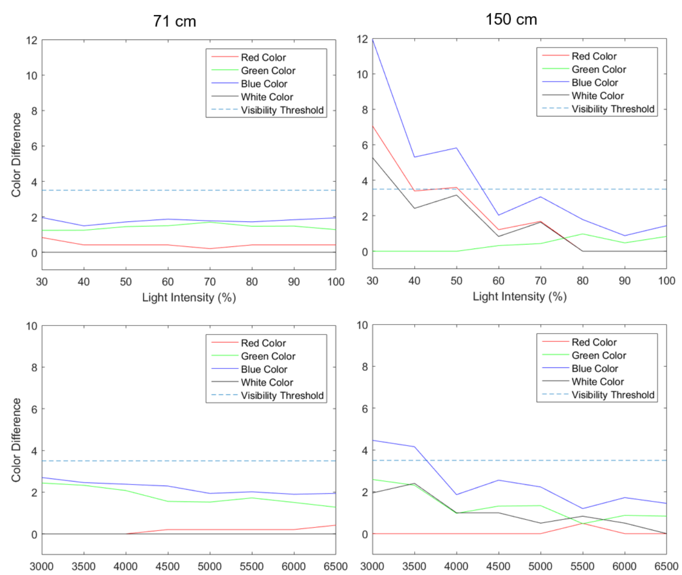
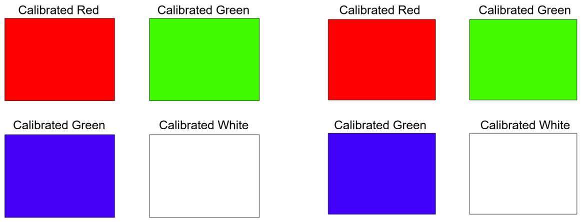


Fig. 10: Detection Accuracy at 71 cm and 150 cm



(a) $5 \leq$ error ≤ 12 (b) error <3.5

Fig. 11: Color errors greater (a) and lower (b) than 3.5.

Figure 10 shows the system's accuracy at both distances. We can observe that the color difference is not noticeable with a light intensity greater than 60% (at 6500K), or a color temperature greater than 4000K (at 100% intensity). To visualize the error in the detected colors, Figure 11 shows estimations with color differences of 5 for white, 7 for red, and 12 for blue; and estimations where the color difference is less than 3.5. As we can see, the difference is not significant, and thus, Lux-Tune will still be able to select the correct color temperature among the nine standard options [7].

Maximum detection distance. We increase the distance beyond 1.5 m to identify the maximum operational distance. At 75% intensity, the system is still functional at 3 m. That is, the system can detect the right tint but not the exact color, so the temperature still matches the needs to increase the appeal of the product. If the luminaire's intensity decreases further or the distance increases, the system fails: the provided temperatures do not match the desired values anymore.

Effect of ambient light. In addition to a tunable luminaire, other lamps can be present in an environment, and although not common in indoor retailing, sunlight may be present too. It is central to analyze the effect of these sources of interference.

To analyze the effect of *artificial lights*, we use the four lamps present in the office. The objects used for this experiment are the same as in Figure 2 (nine different colors). First, with all four lamps off, we calibrate the system. Under this setup, the colors are detected correctly, as expected. Then, without recalibrating the system, (i) we turn on the two more distant lamps (the light intensity changes from 40 to 62 Lux), and the system is still able to provide correct temperatures for all objects; after that, (ii) we turn on the closest two lamps (the light intensity changes from 40 to 113 Lux). Now the system cannot detect the turquoise color well and provides a wrong temperature (4800K instead of 5000K), but it still works well for the other colors. We repeated this process at different dimming levels and found that Lux-Tune can provide the correct temperature as long as the intensity of the interfering signal is less than 50% of the luminaire's intensity.

To analyze the impact of *sunlight*, we set up system next to a big window. The experiment is conducted at three different times: morning, afternoon and evening. Without re-calibration, Lux-Tune does not work well. For example, if we calibrate the system in the morning and test it in the afternoon and evening; the red, green, and blue objects look (i) all white in the afternoon, but (ii) too dark in the evening. This occurs due to two reasons. First, the scaling factors $\gamma(i)$ estimated in the morning are too high for the afternoon (when sunlight is the strongest), but too low for the evening. Second, the color temperature of sunlight changes from bluish in the morning to yellowish in the evening. This change in color temperature leads to an incorrect selection of the calibration matrices.

Summary. Lux-Tune can provide accurate color estimations for different types of objects for distances up to 1.7 m. For longer distances, the system is functionally correct up to 3 m, that is, while the color detection is not accurate, the tint is, and thus, the correct temperature can still be selected to increase the appeal of the product. The main challenge faced by Lux-Tune is external interference. Adding other light bulbs, after the calibration phase, can change the received intensity and color temperature. If the interference is greater than 50% of the tunable light's intensity, Lux-Tune starts providing incorrect color temperatures. Sunlight poses an even greater challenge because its interference is one or two orders of magnitude higher than indoor lighting. To operate under sunlight, a store would require an external sensor that measures intensity and color temperature in real time to broadcast the right scaling factors and calibration matrices to all sensors. In addition, the system should be tested for a wider range of materials with different reflectivities.

B. *Lux-Track performance*

For Lux-Track, the most important parameter is the accuracy of identifying a person correctly. If the system can do that, tracking is trivial because we know the sensors' locations.

Thresholds. Lux-Track requires a set of predefined thresholds (c.f. Section III), the selected thresholds are shown below.

TABLE II: Predefined threshold values.

Level	Level-1	Level-2	Level-3		
Parameter	T_1	T_2	T_R	T_G	T_B
Threshold	0.8	80	0.9	0.9	0.7

The threshold used in levels 1 and 3 have the relationship: $T_R = T_G > T_1 > T_B$. The reason is that the sensor does not capture blue light as strong as red and green. Thus, at level-3, we should be more tolerant when comparing the blue channel, and set T_B lower than T_R and T_G. At level-1, we use the sum of the RGB channels, so the threshold T_1 must also take into account the lower sensitivity in blue colors. Regarding level-2, we use a large value for T_2 because light is not evenly distributed in indoor spaces (it is stronger when a person is directly underneath a light bulb). This means that the same person will have slightly lighter or darker estimations of the true color at different locations. Based on these five thresholds, we evaluate Lux-Track in three main ways.

Same person, same signature: A person should always be assigned the same signature, else multiple users could be created out of a single person. To quantify this requirement, we perform experiments at two different times of the day, 16:30 and 21:30, with two people with similar skin and hair colors. Both wear jeans and the main difference is that one wears a blue-green jacket and the other a blue jacket. Both persons walk through the 2-sensor system 24 times, effectively generating 48 signatures. Table III summarizes the results.

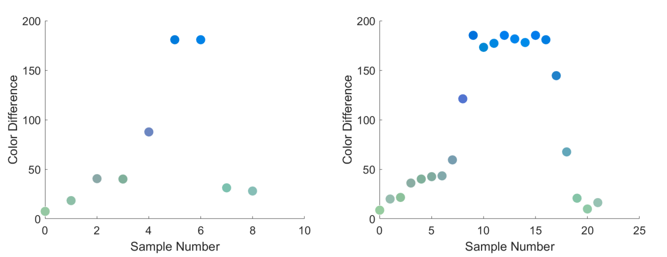
TABLE III: Identification Accuracy

	Blue-green Jacket	Blue jacket
16:30	83.3%	94.4%
21:30	100%	96.3%

These results show two main trends. First, the identification accuracy is higher during the night. This occurs because at the end of the aisle there are windows that allow sunlight to interfere with the system during the afternoon. Second, in the afternoon, the identification accuracy of the person wearing the blue jacket is higher than the person wearing the blue-green jacket, but the outcome is the opposite at night. This occurs because the jackets' materials are different. The blue-green jacket reflects more light than the blue jacket, which causes sunlight to have a greater impact (more noise). Without sunlight (at night), the detection accuracy of the blue-green jacket is higher because it still reflects more light, but in this case it is only indoor light (higher signal to noise ratio).

Different persons, different signatures: This experiment assess how good the system is in differentiating people based on their clothing, from somewhat similar to very similar. The evaluation is performed late at night to avoid interference from sunlight. Three people wear different clothes: blue-green jacket, blue jacket, and white T-shirt (all wear jeans). They walk through the 2-sensor system 17 times, 12 times, and 6 times respectively (on both directions each time), effectively generating 70 signatures. The system is able to distinguish these three people with 100% accuracy. Then, we consider two people differing only slightly in the color of their jacket: one person wears a blue jacket and the other a dark blue sweater. They walk through the system 35 times in turns (both ways), resulting in an accuracy of 91.4%.

Different movement speeds: The speed of a person determines how many samples can be obtained, and therefore, the identification accuracy. By applying DTW, Lux-Track can match signatures with different lengths (speeds). For example, our system is able to match the signatures shown in Figure 12, where a person passes the first sensor without stopping, but stops in the middle of the coverage area of the second sensor.



(a) Passes by the sensor directly (b) Stays in the middle for a while

Fig. 12: The same person passes a sensor with different speeds

However, due to the limited sampling speed of the color sensor (512 ms for the integration time), there is an upper bound for the walking speed. By conducting a series of experiments, we find out that the fastest speed that our current system can handle is 0.67 m/s. Beyond this value, the optical signatures contain only four points, too few to be unique. This maximum speed can be increased by setting up the system in a more illuminated location. Usually non-working environments, such as the corridor, are illuminated with 200 Lux and working office spaces with 500 Lux. We tested the system in an office and observed that Lux-Track can detect a person well because the integration time can be reduced to 128 ms. With this integration time, the system can assign a unique signature to people with movement speeds up to 1.4 m/s.

Summary. Lux-Track is able to map optical signatures even when people have very similar clothing. A limitation of the system is the low sampling rate, which can create few samples if a person walks fast. Also, similarly to Lux-Tune, the system is affected by sunlight. Besides those two points, Lux-Tune has another important limitation: if a person takes off her jacket, or the color of the floor changes in the area of interest, the system could identify a single person as different ones. Further research is required to tackle these shortcomings.

VI. Related Work

Color Detection. The state of the art of color detection can be divided based on the type of sensor used (photodiode, color sensor, or cameras). Table IV summarizes the key differences between the *most relevant* SoA and our work.

TABLE IV: SoA: Color detection

	Lighting	Detector	Range
[10]	constant	photodiode	within 10cm
[11]	constant	color sensor	within 29cm
[12]	constant	color sensor	2.54cm
[13]	constant	color sensor	2cm
[14]	variable	camera	2m
Lux-Tune	variable	color sensor	1.5m

Photodiodes alone are, in principle, not designed to detect colors (only light intensity), but Moghavvemi *et al.* uses a controllable RGB light source to detect colors with photodiodes [10]. The system is only able to differentiate eight colors at a range of 5 to 10 cm. Cameras sit at the opposite side of the spectrum, they have ranges of meters and do not require constant lighting conditions. Al-Bahadly *et al.*, for instance, present a color-based system to detect cars [14]. Cameras, however, are resource-hungry and pose privacy concerns. Color sensors hit a middle-of-the-road spot, they are almost as simple as photodiodes, but they provide color information. Several studies have used color sensors for a wide range of applications, such, detecting the color of walls [11], to monitoring chemical processes based [12], and analyzing healthy plant growth by measuring the plant's leaf color [13]. Our work, builds upon the well known calibration frameworks used for color sensors in the SoA (white balancing and calibration matrices), but we perform a more careful analysis considering longer ranges (more than 1.5 m vs less than 30 cm) and variable lighting conditions – most SoA studies assume constant lighting conditions throughout the testing phase.

Tunable White LED. Tunable white lighting technology allows users to adjust the color temperature of luminaries [15], which can be used to improve the productivity of people in offices or the well-being of patients in healthcare facilities

TABLE V: SoA: Light-Based Indoor Positioning

	Passive Light	Passive Object	Identification Accuracy	Positioning Accuracy
[18]	No	No	High	decimeter
[19]	No	No	None	meter
[20]	No	Yes	None	zone (several mtrs)
[21]	Yes	No	High	zone
[22]	Yes	Yes	None	zone
[23]	Yes	Yes	None	zone
Lux-Track	Yes	Yes	Medium	zone

[16]. We are not aware of any study that provides **automatic** tunable white lighting. In fact, our work is motivated by an *internal* project at a lighting company which requires a camera and the manual selection of the area in which the object is located in order to adjust the color temperature [17].

Light-based Indoor Tracking. Most light-based positioning systems require either modifications of the light source (active source) or people carrying a receiver (active object). Lux-Track is privacy-preserving and fully *passive*, we exploit default lights and people do not need to carry any receiver. Table V provides an overview of various methods in the SoA.

Active Source, Active Object. In these systems, light bulbs act as anchors transmitting beacons, and cameras [18] or photodiodes [19] decode these beacons to obtain decimeter-level and meter-level positioning, respectively. While accurate, these systems require light bulbs to be modified and the users to carry a receiver with line-of-sight to the light bulbs.

Active Source, Passive Object. Other systems modify light bulbs to detect occupancy without requiring users to carry any electronic device [23], [20], [24]. Those systems place simple photosensors in the environment to measure perturbations in light reflections caused by people. Motivated by these studies, Lux-Track also exploits reflection but for a more complex task (identification not just presence), and without requiring any modifications to the light sources.

Passive Source, Active Object. More recent efforts provide indoor positioning systems without the need to modify lights sources. The key idea is to exploit the signal strength or inherent features radiated by standard LEDs [25]. These systems have great potential because the overhead is low (no need to modify the lighting infrastructure), but the users need to carry a photosensor with line of sight to the luminaries.

Passive Source, Passive Object. To avoid the need of modifying lights or requiring users to carry receivers, some studies are deploying photosensors, coupled with battery-less radio transmitters, to detect light fluctuations in order to provide occupancy and location information [22]. Lux-Track also focuses on low overhead scenarios (unmodified light and users without receivers) but provides a more advanced and challenging feature: identification.

VII. Conclusions

We propose using color sensors for two novel applications. First, Lux-Tune, a system that can accurately detect an object's true color and adjust the illumination temperature to make it more appealing. Lux-Tune works at significantly longer ranges compared to the SoA and at variable lighting conditions. Second, Lux-Track, a system that relies on single-pixel information to provide anonymous tracking. Lux-Track can identify persons even when their clothing are rather similar.

This is a preliminary study on a rather small number of people and with limited scenarios. The robustness of the system needs to be tested on a larger scale, taking into account the real environments the system is aimed to be used at — retail stores. For those scenarios, more complex signal processing algorithms and methods may be required. We hope that this work will motivate the research community to look deeper into color sensors for various IoT applications. These sensors offer a promising means to capture visual information related to human perception, and are a cheaper and more privacy-protective alternative to cameras.

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