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Indoor Localization Using Multi-Color Fingerprinting

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Abstract—VLC based indoor positioning system is a natural choice thanks to LED technology and future trend. We can reuse existing LED lighting installations to design an appropriate scheme to provide indoor localization. By receiving basic information such as the light intensity and knowing the position of the transmitters for example through Visible Light Communication (VLC), one can estimate its position with the potential of high accuracy. In this paper, we use a multi-color sensor and build an indoor localization system based on the light fingerprint, which is suitable for smart cities and homes, health-care centers, hospitals or similar. There are, however, several practical problems that make it a technology that is not yet sufficiently developed to be used in our everyday life. In this paper, a new perspective is given by looking into indoor localization using multi-color fingerprinting and different machine learning methods. Experiment results have shown its effectiveness and potentials with mean localization errors of around ten centimeters.

Index Terms—Indoor positioning system, VLC based localization, fingerprint, smart cities and homes, health-care centers and hospitals.

I. INTRODUCTION

Indoor localization techniques play a fundamental role in many emerging applications [1]–[3], such as human/object tracking, robot navigation, smart cities and homes, health-care centers and hospitals, location based information transmission [4], digital twins, and Industry 4.0. Large buildings often have complex indoor structures which force unfamiliar visitors to struggle to find their bearings and getting where they need to be. Besides, asset and patient/people tracking in hospitals and various environments become more and more important, among others for the sake of efficiency or safety, for example regarding possible infection between patients or accident prevention and detection. In light of the modernization happening throughout the entire health sector, indoor localization becomes an especially interesting topic. A good indoor localization system can help in such situations, speeding up navigation and improving the overall user experience.

The Global Positioning System (GPS) is capable to localize devices globally with a precision of around one to ten meters in most cases. This is sufficient for a large number of applications, outdoor navigation and freight tracking being the most popular. However, GPS is not suitable for indoor use due to the severe attenuation of satellite signals and the lack of line-of-sight [5]. Besides, there are situations and applications in which this level of precision is simply not sufficient. For example, in indoor localization, an error of two or three

meters may mean an entirely different room. Although high-sensitivity GPS has been proposed to enhance the precision and provide some indoor coverage, its accuracy is still not satisfactory [6].

Several approaches exploit popular Radio Frequency (RF) technologies such as Wi-Fi and Bluetooth for indoor localization [7]. One of the interesting results is the Wi-Fi based positioning system (WPS) [8] which uses the fingerprint of existing Wi-Fi networks for user localization. It is also interesting that Bluetooth beacons can be used similarly to provide localization at accuracy around two to three meters with the advantage of having low cost and low power consumption. Other technologies include infrared (IR), radio-frequency identification (RFID) [9], ultrasound, wireless sensor networks, ultra-wideband communication (UWB), magnetic signals, user movement [10], and inertial measurement based methods [1].

Over the last few years, indoor localization using visible light has gained much attention in the research community. This rise in popularity can be explained by two main reasons: the need for precise and affordable indoor localization solution and the trend of global implementation of Light-emitting Diodes (LEDs). LEDs have some very interesting characteristics for a number of purposes. They are more energy efficient than traditional lighting, have a longer life expectancy and can be modulated at high frequency. In contrast to other positioning systems, visible light based solutions have several advantages: First, the accuracy can meet the demand of high resolution indoor localization [11], while the cost is low as the lighting infrastructure already exists and the use of visible light spectrum is license free. Second, visible light based systems are eco-friendly as we can use LEDs as the transmitters which are very energy efficient and do not cause electromagnetic interference. This is especially interesting in settings, where sensitive equipment is used that might suffer from interference, such as medical equipment. Also, due to the wide scale proliferation of LEDs and its emerging development for VLC [12], visible light based localization has been examined actively.

In this paper, we will focus on localization using light measurements over different wavelengths, meaning different colors, and in our experiment the red, green and blue (RGB) for simplicity. Even though the LEDs in use are emitting white light over the whole visible light spectrum, common light sensors [13] can easily differentiate light intensities at their different wavelengths. We investigate the use of multi-

color fingerprint for indoor localization and apply several interesting algorithms to compare and build our system. The main contributions of our work can be summarized as follows:

- 1) Demonstration of the feasibility of visible light fingerprinting based localization built on machine learning techniques for accurate positioning in noisy environment,
- 2) Analysis of the impact of using multiple colors as opposed to today's common practice of simply using one single wavelength,
- 3) Evaluation of the localization errors to expect using a low-cost solution through experiment work.

The rest of this paper is organized as follows. In Section II, we discuss related work of visible light based positioning methods. Section III describes our system design and the algorithms. Section IV shows the experiment setup and obtained results. Finally, Section V contains some concluding remarks.

II. RELATED WORK

There are several approaches that exploit visible light to perform indoor localization, many of which have been studied in the literature. Almost all of them are based on the underlying assumption that the receiver can differentiate among light sources: this can be realized by having the LEDs working in a transmission multiplexing scheme such as Time Division Multiple Access (TDMA) and Frequency Division Multiple Access (FDMA), which are common technologies. Discussions of the advantage and disadvantage of these multiple access schemes for VLC can be found in [14].

In the following, we describe the four main visible light based positioning approaches: proximity, triangulation, trilateration and fingerprinting.

A. Proximity

Visible light positioning based on proximity is the simplest and least precise approach. It rests solely on the main assumption that the receiver can distinguish between different transmitters. A possible implementation of this could be a building in which each room has a LED that is modulated at a different frequency to identify itself, therefore a receiver that finds one predominant frequency in the ambient light can easily know in which room it is situated based on a known mapping between rooms and frequencies. A detailed investigation of this approach can be found in [15].

B. Triangulation

With triangulation, a receiver uses the incoming light's Angle-of-Arrival (AOA) to determine its position relative to the LEDs. The most straightforward way to determine the incoming light's AOA is to use an array of co-located photodiodes [16]. The coordinates of the receiver can then be determined according to the estimated arrival angles. Hybrid schemes may exploit the availability of other sensors (such as accelerometer [17]) for deriving the receiver's location.

C. Trilateration

Trilateration is conceptually similar to what is done in GPS. In the first step, the receiver estimates the distance to each of the transmitters. Once there are distance estimates from a sufficient number of transmitters, generally at least three or four depending on the algorithm, these distances can be used to estimate the device's position in relation to the transmitters. To estimate the distance, we can measure the Received Signal Strength (RSS) and use a path-loss channel model to determine [18], or measure the Time-of-Arrival (TOA) to calculate the distance relatively to the speed of light. Note that if TOA is required, an accurate time synchronization between the LEDs and the receiver would be needed.

D. Fingerprinting

Fingerprint-based localization compares the received information with a known information map to estimate the user position. There are three popular fingerprint based indoor localization methods [11], namely probabilistic method, k -nearest-neighbors, and neural networks.

For example, in [19], user location is estimated through the best matching between the received light intensity and light fingerprint of modulated LED beacons collected during a training phrase. Besides, localization can be done by various sensor fusion techniques with classifiers using machine learning on the RSS of LEDs [20]. Note that in practical scenarios, each LED may transmit an identification code for example in time division multiplexing in order to distinguish itself from one another for receiver's localization.

III. SYSTEM DESIGN AND ALGORITHMS

In this section, we present our localization system and fingerprint based solution through three different methods. The details are given below.

A. System Design

We use a prototype embedded sensing device which is equipped with a multi-color sensor capable of measuring the intensities of red, green and blue (RGB) components of a light source simultaneously. Each time a measurement will be taken it consists of the RSS values of the light. We deploy a number of LEDs, denoted by L , that emit light in a time division multiplexing fashion. Let's denote the number of colors measured at the sensor (the receiver) by C . The total number of RSS measurements is then given by $L \cdot C$. These measurements will later also be referred to as *features*. Given the nature of fingerprinting based localization, our scheme consists of the following two phases:

- 1) Training (offline) phase,
- 2) Localization (online) phase.

During the training phase, data collection has to be performed, meaning that color intensity measurements are taken at known positions and stored in a database. Whenever "position" is mentioned in the following sections, it refers to a location (x, y) in the XY-plane, with x -coordinate and y -coordinate to be estimated while the z -coordinate is being

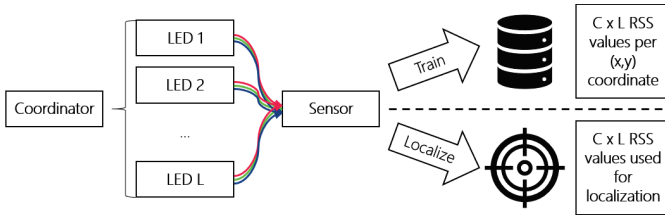


Fig. 1: System overview

considered constant and known. We consider for example the sensor is attached to an unmanned ground vehicle (UGV) or machine for a modern health-care center or hospital application.

During the localization phase, the sensor measures RSS values for all the LEDs and uses them as input for an algorithm, which in turn outputs a position estimate. Fig. 1 depicts the basic system. In our experiment work in Section IV, we use an Arduino [21] as a coordinator to control the transmission (on/off) activity of LEDs in time division multiplexing.

B. Algorithms

As aforementioned, the system presented in this work is fundamentally based on the fingerprint of RSS in different places, received from different LEDs. We collected the RSS measurements during the training phase and apply three different algorithms applied during this work for the indoor localization: k -Nearest-Neighbors, Neural Networks, and Decision Trees. We will explain each of them in the following. All of them can be implemented in Python using Scikit learn [22]. Note that all these algorithms operate with the same training data set of same size N , while each of these training points has its position as *label* and a constant number of *features*, meaning the RSS measurements per LED and per color. The number of features is thus $L \cdot C$, where L is the number of LEDs and C is the number of colors.

1) *k-Nearest Neighbors*: kNN is a deterministic machine learning algorithm that takes an input and tries to find the best matched point or points in the training set. The metric used to evaluate the similarity can vary, however, most often a simple Euclidean distance over all the features is used. In the case of Euclidean distance, the score for each training point can be determined using (1) for user localization, where F is the number of features while t and m denote the training point and the current measurement, respectively.

$$D_{t,m} = \sqrt{\sum_{f=0}^F (t_f - m_f)^2} \quad (1)$$

The value of k defines the number of points to pick during the best fitting. For localization purpose, we take these k best fits regarding the RSS, i.e., with the lowest value of $D_{t,m}$, and calculate the estimated position as average over the (x, y) coordinates of these k points. However, it is worth noting that one can also consider to calculate a weighted average through some weighting functions, see for example [23] and references therein.

2) *Neural Networks*: Another algorithm that we employ is a neural network (NN). For example, in [24], the authors use a neural network for localization through wireless sensor networks (WSN) in indoor environment. In our system, the Neural Network (NN) has $L \cdot C$ input neurons and 2 output neurons accordingly, one for the x -coordinate and one for the y -coordinate. Given the relatively small amount of data present throughout the experiment (see Section IV), the NN can have a fairly simple structure, meaning one hidden layer containing 8 to 100 hidden nodes.

Note that our NN training is done using random initialization values and backpropagation. This means that for small training set size, as it is the case in our experiment, the NN might not perform in the same way every time. However, this should not matter much in the long run. For a bigger number of training samples, this can be negligible. On the other hand, in the case of few training points, a bigger number of NNs can easily be trained and the average estimate of these networks can be used to alleviate the problem.

3) *Decision Tree*: Decision tree learning is a kind of non-supervised machine learning algorithm that can be used for either regression or classification [25]. In our work, it is used to perform regression with regard to x - and y -coordinates. A decision tree is trained by performing binary decisions along singular features, while minimizing the error judged by some criteria. In our case, it is to minimize the mean square error (MSE) of the estimated position.

C. Normalization

As it is the case with most machine learning algorithms, the above three algorithms also require normalized or scaled input data [22]. There are different ways to normalize or standardize the data for machine learning. Let's use $\mathcal{V} = \{v_i\}$ to denote all the values of a given feature (i.e., its RSS values at different places), whereas v_i is one single value, where $i = 1, 2, \dots, |\mathcal{V}|$.

One way is to use a min-max normalization for each feature, applying the transformation depicted in (2), where v'_i is the normalized value of v_i . Another way is the z-score normalization, which is given by (3), where $\sqrt{\text{Var}(v_i)}$ refers to the standard deviation of v_i . In this work, we will adopt the min-max normalization since it appears to work better for the measured data from our experiment observation.

$$v'_i = \frac{v_i - \min(v_i)}{\max(v_i) - \min(v_i)} \quad (2)$$

$$v'_i = \frac{v_i - \text{mean}(v_i)}{\sqrt{\text{Var}(v_i)}} \quad (3)$$

IV. EXPERIMENTAL SETUP AND RESULTS

We now show the experimental setup and present the obtained results following the system design and methods aforementioned.

A. Transmitter Design

The transmitter system is a common design which is similar to many in the literature and easy to implement (see for

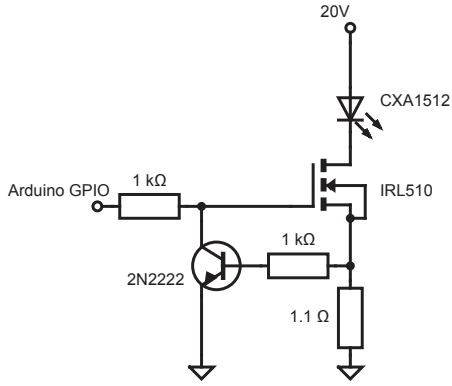


Fig. 2: LED driver circuit

example [17]). We deploy a fixed number L of LEDs which light up in a round-robin time division multiplexing manner. Each period is divided into $L + 1$ time intervals (slots), where the first interval serves to synchronize the receiver with the transmitter. In the subsequent time intervals, exactly one LED is emitting light at any given time. This allows the receiver to measure the LED light intensity from each source without the disturbances caused by the other LEDs. To achieve this, the LEDs are connected to a central coordinator (controller).

In our experiment, four LEDs (CXA1512-0000-000FOHM450F [26]) are used and we use an Arduino Mega 2560 [21] as the central controller. The driver circuit for each LED is shown in Fig. 2. To allow switching that is not perceptible to human eyes, the transmitter system allows switching frequencies of up to 1 kHz.

Note that since our work is a fingerprinting based solution, there are only few constraints regarding the LED. Obviously, they need to emit sufficient light to be easily detected by the receiver (sensor), but beside this, any LED supporting high-frequency switching is fine to use. In addition, it is not even necessary to use the same model or to have them all at the same brightness.

B. Receiver

One of the interests of this work is to examine the impact that the measuring of different colors can have on the fingerprint based localization. Hence, the receiver used has to be able to measure the light intensities at different wavelengths. In this work, we use a light sensor integrated hardware platform developed by Nokia Bell Labs, called Gecko, which contains a common color sensor (BH1749NUC [13]) that can measure the red, green and blue light intensities emitted from the LEDs. It is a rechargeable battery powered device with solar panel operating in low power consumption and can connect via Bluetooth for communications to allow for easy data collection.

C. Experimental Setup

The experiment and data collection has been executed in an office/work environment, as seen in Fig. 3. It is to be noted that



Fig. 3: Experimentation area

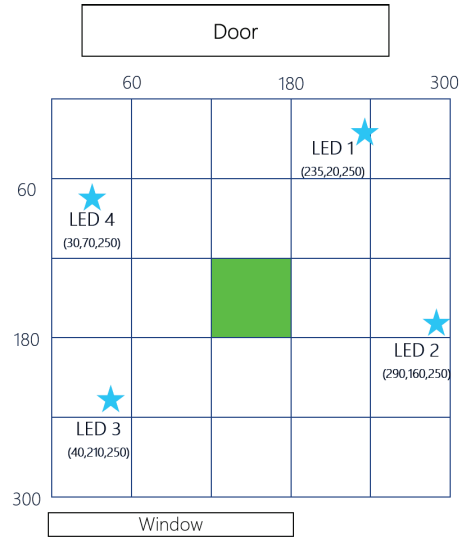


Fig. 4: Floor plan (all distances in cm)

during training and localization, the ceiling lights remain on, thus corresponding to a constant noise to the measurements taken for the respective LEDs. Furthermore, the office does have a window, which further introduces a weather-dependent disturbance due to the sunshine coming from outside. For this, all the measured data are stored alongside the information of its time of day.

Fig. 4 shows the floor plan of the experimentation area. The measurements are concentrated in a central area, which is highlighted in both Fig. 3 and Fig. 4. The fingerprint maps out a $60 \text{ cm} \times 60 \text{ cm}$ area, divided into a grid with 5 cm step size, resulting in a total of $N = 169$ positions. Given that there are four installed LEDs ($L = 4$) and that the light sensor provide us the RGB measurements ($C = 3$), we have in total M measured values as input to the algorithms during the training phase which is conducted at noon, where $M = N \cdot L \cdot C = 2028$.

TABLE I: Localization error evaluated at noon

	kNN				Neural Network				Decision Tree			
	<i>R</i> -only	<i>G</i> -only	<i>B</i> -only	<i>RGB</i>	<i>R</i> -only	<i>G</i> -only	<i>B</i> -only	<i>RGB</i>	<i>R</i> -only	<i>G</i> -only	<i>B</i> -only	<i>RGB</i>
Mean error (cm)	14.7	13.4	14.2	13.0	12.2	11.2	11.7	10.8	17.0	15.6	17.0	14.7
Max error (cm)	44.9	41.9	53.9	49.5	43.8	41.7	50.2	46.8	58.1	44.1	52.9	52.2
Min error (cm)	1.4	1.4	2.0	1.0	0.0	0.0	0.0	0.1	1.4	0.9	1.5	0.7
Std deviation (cm)	8.6	7.9	8.8	7.8	7.7	7.0	7.3	6.5	11.0	8.9	9.5	9.0

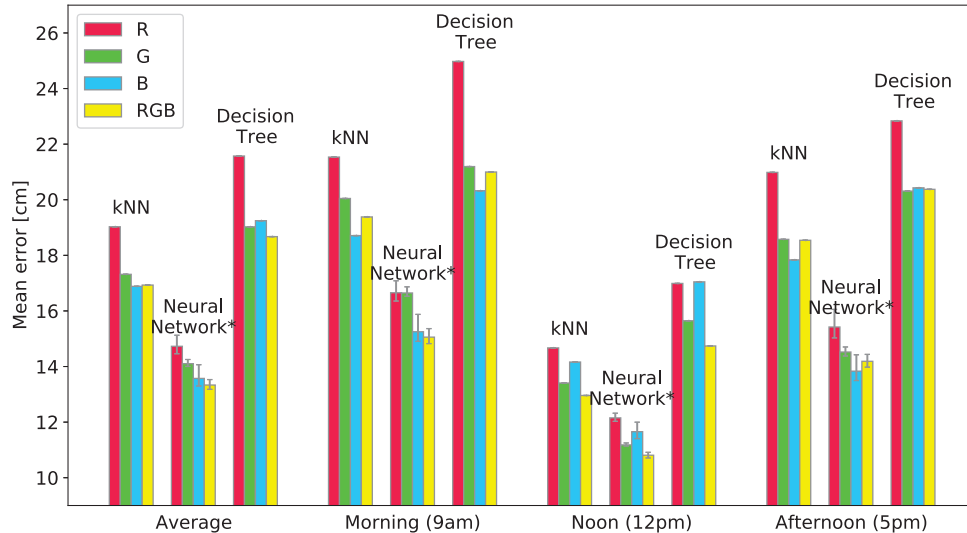


Fig. 5: Mean localization errors by time of day, algorithm and colors used. Fingerprint for training phrase was taken at noon. (Quartiles of 1500 different neural networks are marked to evaluate the impact of random initialization value during training.)

D. Results

We evaluate the performance of the system during the localization (online) phase. Measurements are taken at different positions in the highlighted area in Fig. 4. These tests are carried out at different times of day: during the morning (between 9 and 10 am), noon (between 12 and 1:30 pm) and afternoon (between 4 and 5:30 pm), respectively. The localization is conducted, using different inputs for performance evaluation and comparison: either all the three colors or only one color among them. Comparing the localization estimate with the ground truth, the error of each estimate is taken, which is calculated by the square root of the mean square error (MSE) of the estimated position. The mean, minimum and maximum as well as the standard deviation of the localization errors for the different algorithms and inputs collected at noon are shown in Table I.

There are some interesting observations from Table I. Firstly, comparing the mean errors, the neural network seems to have the best performance on average. For all inputs, the neural network’s errors are the smallest. This supports a hypothesis that this kind of fingerprinting problem can be treated as a regression problem. Secondly, when comparing the different inputs, it appears to be helpful to use the three different colors combined. For every single one of the algorithms examined, combining the different colors leads to a decrease in the mean error. Thirdly, the colors seem to not be equivalent in localization performance: disregarding the combination of

RGB, green seems to be the color which leads to the best result. Note that our LEDs emit white light, meaning that the different color components are highly correlated at the source. The fact that the combination of them leads to a higher precision can be explained by the higher measurement diversity, i.e., more samples generally lead to better result. However, the fact that one color works better than the other in the above indicates that the noise that is being introduced is not equivalent for each color, thus supporting the interest in examining multiple colors. In terms of the variance of localization errors, the neural network also outperforms the other algorithms. Besides, it has both the smallest maximum errors and the smallest minimum errors.

Fig. 5 shows the localization error performance, grouped by different times of day (“Morning”, “Noon” and “Afternoon”, resp.) and the average over them (“Average”). We can see that the localization errors around noon are the smallest as expected since the training data have been collected at noon as aforementioned. The errors go up by a few centimeters for different times, however, they still seem to be reasonably good in general. In almost all our examined cases, the average precision increases when using RGB as input for the algorithms. On the other hand, the neural network is the best fitting algorithm among the three algorithms.

Table II presents the mean, minimum, maximum and standard deviation of the localization errors, taking into account the tests at different times of day. Looking at all the data, the

TABLE II: Localization error averaged over all the times

	kNN				Neural Network				Decision Tree			
	<i>R-only</i>	<i>G-only</i>	<i>B-only</i>	<i>RGB</i>	<i>R-only</i>	<i>G-only</i>	<i>B-only</i>	<i>RGB</i>	<i>R-only</i>	<i>G-only</i>	<i>B-only</i>	<i>RGB</i>
Mean error (cm)	19.0	17.3	16.9	16.9	14.7	14.1	13.6	13.3	21.6	19.0	19.2	18.7
Max error (cm)	51.7	52.9	53.9	50.0	44.3	42.9	55.4	46.8	58.1	60.8	52.9	53.0
Min error (cm)	1.4	1.4	1.0	1.0	0.0	0.0	0.0	0.0	1.4	0.9	1.5	0.7
Std deviation (cm)	11.3	9.5	9.9	10.0	8.9	7.9	7.7	7.7	13.4	10.7	10.8	11.1

key observations from before still hold true, for example the neural network has the lowest mean, minimum and maximum errors and also the smallest standard deviation, among the three algorithms. However, comparing the performance for single colors, it becomes apparent that it is not always the same color having the lowest error. This indeed favors to combine multiple colors for diversity combining. Table II also shows that using RGB as input in general outperforms.

V. CONCLUSION

VLC based indoor localization is a promising solution in a variety of settings and emerging applications, including smart cities and homes, health-care centers, hospitals or similar. There are, however, several practical problems that make it a technology that is not yet sufficiently developed to be used in our everyday life. In this paper, a new perspective is given by looking into indoor localization using multi-color fingerprinting and different machine learning methods. Using a simple, low-cost hardware setup and experimented under noisy environment, we have shown its feasibility and the approach can achieve a localization accuracy of around 10 cm on average, which has high potential for many applications. Besides, it stands to reason that this precision can be improved further by advancing the system setup and hardware devices. One can also expect performance improvement by including some other signal processing methods. Among the three algorithms, the neural network appears to be the most promising scheme in our case. Meanwhile, we have shown a solid baseline of a minimal performance gain to be expected by using the light measurements at different wavelengths in the localization.

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