Watchers on the Wall: Passive Visible Light-Based Positioning and Tracking With Embedded Light-Sensors on the Wall

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***Abstract*— This article reports a novel visible light positioning (VLP) system and the associated experimental results. The developed VLP system is completely passive as it does not require a tracked object to carry any active device or tag. At the same time, it does not require any modification to the existing lighting infrastructure. The positioning system, termed Watchers on the Wall (WoW), localizes a target based on measuring the change it creates in the received signal strength (RSS) of the ambient light recorded at an array of light-sensors embedded in the wall. A prototype system has been implemented and tested to investigate the performance of the proposed approach with regard to localization and tracking. The experimental results show that the median and 90-percentile localization errors of 7 and 21 cm, respectively, can be achieved for a 2 m × 3.6 m testbed. The effect of various parameters like the height of placement and the number of light-sensors, as well as the size of the fingerprint database, has also been studied. The impact of various distance metrics on the localization performance of the weighted K-nearest neighbor (WKNN) classifier has been investigated. It has been found that two distance metrics outperform the commonly employed Euclidean metric. The experimental results also demonstrated that the developed system could track a mobile target along multiple routes with a median error of 12 cm.**

***Index Terms*— Device-free localization (DFL), indoor localization, indoor positioning system, passive visible light positioning (VLP), VLP, weighted K-nearest neighbor classifier (WKNN).**

I. Introduction

INDOOR positioning has been a burgeoning area of research over the past decades. In terms of outdoor positioning, GPS [1] is the de facto solution, due to it being both ubiquitous and free to use. However, it has limitations, especially in built-up areas or indoors [2]. The GPS signal is adversely impacted by multipath reflections and struggles to penetrate walls. Furthermore, the offered accuracy of several meters [3] is not good enough for indoor applications. For these reasons, other methods have been proposed. They have been based on the use of Radio Frequency Identification [4], Bluetooth [5], Wi-Fi [6], ZigBee [7], UltraWideband [8], Magnetic Fingerprinting [9], and Ultrasonic [10] to mention the most popular. While the majority of these represent an improvement over GPS for indoor localization, they often do not provide the desired levels of accuracy, reliability, or simplicity. With light emitting diodes (LEDs) steadily replacing the traditional lighting sources, a new method of positioning has come to the fore–Visible Light Positioning (VLP) [11]. Visible light has the benefit of being far less susceptible to multipath interference and flat fading due to its vastly higher frequency than radio frequency signals [12]. LED lighting can also perform multiple roles–illumination, communication, and positioning. Active VLP has been well researched. It relies on a mobile object having a receiver containing either a photodiode (PD) or an image sensor [13]. There are several active VLP methods that have been implemented on indoor testbeds, with the main approaches being Received Signal Strength (RSS) Lateration [14], [15], Angle of Arrival Angulation [16], and Fingerprint Matching [17].

Passive positioning or Device-Free Localization (DFL) [18] allows for object detection without the need to have any receiving device attached to the tracked object. Potential applications of such localization systems could include location-based services in smart buildings, business analytics for retail applications, emergency evacuations, accessibility aids for visually impaired persons, and fall detection in rest homes. DFL systems based on wireless technologies have been investigated extensively in the last decade. The current wireless-based DFL solutions using Commercial-Off-The-Shelf (COTS) equipment require a significant number of wireless nodes while offering a median accuracy of approximately 1 m [19]. Recent works employing the customized hardware and the *channel state information metric* have shown promising results with the median localization error as low as 0.35 m in *line of sight* human tracking scenarios [20], [21].

While DFL systems based on wireless technologies have been widely reported in the literature, there are only a handful of existing works dedicated to passive VLP [22]–[30].

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However, just like its active counterpart, passive VLP can potentially be significantly more accurate than the wireless passive positioning techniques. Consequently, there is a need to develop advanced passive VLP solutions.

Collocated LED luminaires and PDs have been applied to passively detect humans in [22]. The light from the LED luminaires was multiplexed using *Time-Division Multiple-Access* to identify the source of incoming light at each PD. The work primarily focused on investigating the ability to detect whether a door was open or closed. The work was further extended in [23] to track human movement and detect room occupancy. In the research [24], the floor was inlaid with 324 PDs, with five LED luminaires placed on the ceiling above. That setup was then used to detect the position of a human body and limbs from the shadows cast onto the floor. The work was further extended in [25] using only 20 PDs, albeit with a much larger number of LED panels on the ceiling. That simplified the infrastructure at the cost of a slight decrease of accuracy. Similarly, Zhang *et al.* [26] also used a grid of PDs embedded in the floor. LED luminaires on the ceiling cast shadows from test subjects onto the said PDs. However, the article reported results that were mostly based on simulation. The only experimental result reported in the article was a single point-to-point LED to PD link to gather parameters for a larger-scale simulation. In simulations, the authors were able to achieve a median error of 8 cm in an 8 m $\times$ 8 m $\times$ 4 m room with four LED luminaires and PDs uniformly spaced at the distance of 0.5 m on the floor. Zhang *et al.* [27] used a passive VLP approach for mobile device input using one LED and two PDs to detect a user's finger. The application of LED improved the reliability in the presence of changing ambient light. The *CeilingSee* approach [28] employed reverse-biased LED luminaires as PDs for occupancy sensing. However, the authors did not use the system for positioning test subjects or objects. Therefore, they did not report any results on the localization accuracy. Hu *et al.* [29] proposed the use of ceiling mounted photodetectors for accurately sensing the indoor environment change. While this technique can potentially be adopted for occupancy inference and position estimation, no localization and tracking algorithms were reported in the article. In addition, theoretical development was validated with simulation study only, and no practical implementation was done. Another group of researchers reported a passive VLP system that utilized a network of visible light communication (VLC) luminaires and PD-based receivers on the ceiling [30]. The system measured the impulse responses (IRs) between each transmitter–receiver pair similar to the channel sounding approach [31]. The target was localized based on the measured changes of the IRs. The reported rms localization error was based on simulation only, and no prototype development or physical system implementation was done. Table I summarizes the reported research in the area of passive VLP.

This article focuses on achieving accurate positioning of an object under ambient light conditions without the need for any modification to the existing lighting infrastructure (unlike the majority of VLP solutions). Table I frames the work presented in this article with respect to the state of the art in the field.

The work presented here extends the preliminary results reported in [32] and makes the following original contributions.

1) *Novel passive VLP system based on ambient light only:* This is the first implemented passive VLP system that the authors are aware of that does not require any modification to the lighting infrastructure.
2) *Functional passive VLP system with the associated experimental results:* The developed system, termed WoW (shorthand for Watchers on the Wall) requires only cheap PD-based light-sensors embedded in a wall to operate. The developed system was extensively tested to study the impact of various factors on the localization accuracy.
3) *Moving target tracking:* The ability of the developed system to track a moving object was investigated for several routes. As far as the authors are aware, this is the first work that reports the localization accuracy of a passive VLP system while tracking a moving target traversing multiple routes.
4) *Impact of distance metric on the performance of the Weighted K-Nearest Neighbor (WKNN) classifier:* The impact of various distance metrics on the localization performance was investigated. It was found that two distance metrics outperformed the commonly used *Euclidean* metric. To the best of the authors' knowledge, this is the first publication that explores the impact of the distance metric on the performance of the WKNN classifier for passive VLP.

The rest of this article is organized as follows. Section II describes the hardware and data acquisition system of the developed VLP system, introduces the key concept of using RSS as a fingerprint with the aid of a simple proof of concept system, and proposes utilizing the WKNN algorithm for positioning. Section IV presents the localization performance of the developed system. The section also reports the impact of various parameters on the localization accuracy. Section V concludes the article with suggestions for future work.

II. System Development

A. Key Concept

In a room, there are generally multiple light sources: windows, doors, and interior lights. The walls of the room are often lightly tinted, thereby causing a portion of the light to be reflected. A person moving around the room produces several shadows of different intensities projected onto the floor and walls. The major shadows are the results of blocking the direct paths from ambient light sources. However, many other shadows are generated due to multiple reflections and artificial light sources. The shadows can be detected by light-sensors placed around a room as a change in the observed ambient light level, i.e., a change in RSS.

B. Hardware for RSS Data Acquisition

In order to explore the possibility of using the change in RSS for positioning purposes, a simple proof of concept

TABLE I
COMPARISON OF WOW WITH OTHER PASSIVE VLP SYSTEMS

Research	Results Obtained	Receiver Sensor	Modified Lighting infrastructure	Tracking moving target	Limitations
Ibrahim *et. al* [22]	Primarily detected whether a door was open or closed.	PD collocated with LED luminaires	Yes	No	Does not track or localize target.
EyeLight [23]	93.7% occupancy count accuracy, 94 cm median localization error.	PD collocated with LED luminaires	Yes	No	Only works in controlled environment as sunlight saturates the receivers.
LiSense [24]	Mean angular accuracy of 10^0 for the 5 main body joints	Floor inlaid with PD	Yes	No	Does not track or localize target. Needs a large number of PDs
StarLight [25]	Mean angular accuracy of 13.6^0 for the 5 main body joints	Floor inlaid with PD	Yes	No	Does not track or localize target
Zhang *et. al.*[26]	Median error of 8 cm	Floor inlaid with PD	Yes	No	Localization results obtained via simulation only.
Okuli[27]	Position a finger in a 9 cm x 7 cm grid with 0.7 cm median error	Two PD around a tablet	No	No	Does not track or localize a human target. Only positions a user's finger while using a tablet.
CeilingSee [28]	Detected Room occupancy	Reverse biased LED luminaires as PD.	Yes	No	Does not track or localize target.
Hu *et. al.*[29]	Simulation results show the developed algorithm can sense change in environment.	PD embedded in the ceiling	Not specified	No	Does not track or localize. Suggested that environment change can help infer occupancy and position.
Majeed *et.al.* [30]	RMS error is 5 cm	PD collocated with LED luminaires	Yes	No	Requires fingerprinting. Localization results are obtained by simulation only.
WoW (proposed)	Median error of 7 cm for stationary and 13 cm for moving target.	PD embedded within walls.	No	Yes	Requires fingerprinting. Needs to be further developed to work in changing ambient light.

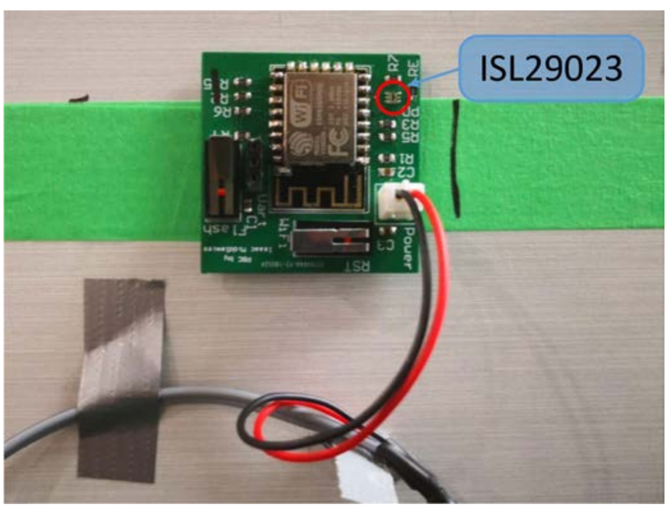


Fig. 1. Custom-designed light-sensor.

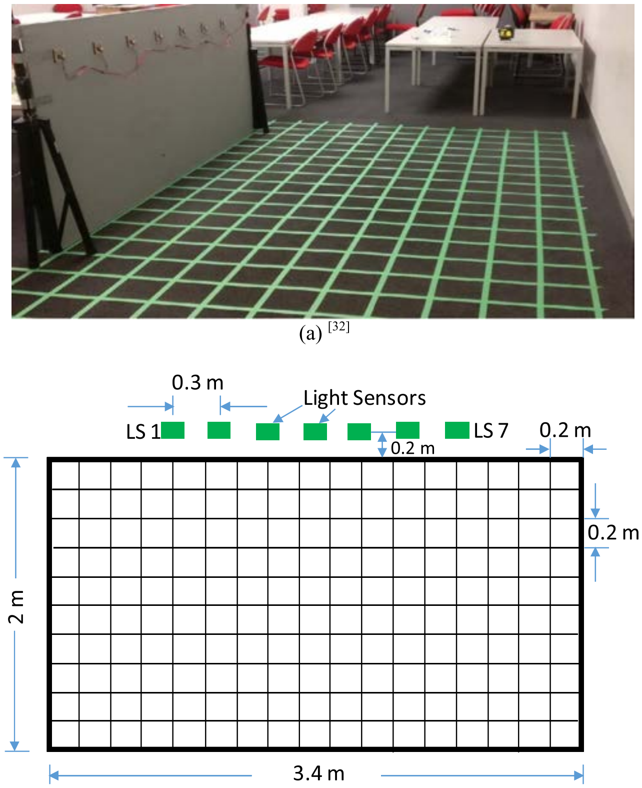
system was set up using ISL29023 [33] integrated digital light-sensors (Fig. 1). The light-sensors comprised a PD, a trans-impedance amplifier, and an analog-to-digital converter (ADC) located in the same package. Each light-sensor was connected to a low-cost Wi-Fi microchip (ESP8266 [34]). The ambient light produces a dc signal at the output of the trans-impedance amplifier. The dc level is a measure of the RSS of the ambient light. It is sampled by the embedded ADC and retrieved by the microcontroller of the ESP8266. The latest 100 samples are stored in the internal memory until they are retrieved over Wi-Fi. The data can then be requested in 100-value packets from a computer and saved to a nonvolatile memory.

C. Proof of Concept Setup

The sensors were placed on a board at a height of 1.05 m from the floor level. A 3.4 m x 2.2 m-grid with 0.2-m squares was marked out using masking tape and a laser straight edge. The sensors were positioned along the side of the grid furthest from the wall, with the PDs pointing back toward the wall. The RSS data were collected at each grid intersection for a total of 198 locations. Each measurement consisted of 100 RSS readings over 10 s at each sensor. The layout of the proof of concept system is shown in Fig. 2.

D. RSS as Fingerprint

The RSS can be used as a fingerprint to locate mobile objects. This can be observed in Fig. 3 for the proof of concept setup. The blue bars are the RSS at the seven light-sensors when the test area is free from obstruction (i.e., moving or stationary target objects). The red and orange bars present two cases when a person is standing in the front left area (i.e., close to the first two sensors on the wall—1 and 2) and then in the back right position (i.e., opposite to the last two sensors—6 and 7). Naturally, greater reductions in the RSS can be observed at the sensors that are closer to the test subject. For example, when the test subject is in the front left position, the RSS drop is more significant for sensors 1 and 2, while there are very little reductions for sensors 6 and 7.



(a) [32]

(b)

Fig. 2. Proof of concept system. (a) Actual setup. (b) Layout diagram.

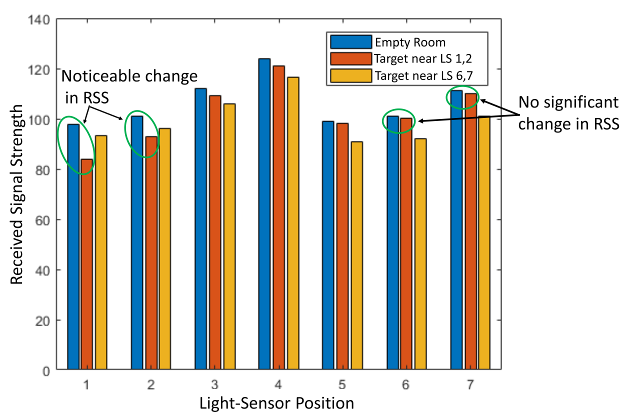


Fig. 3. Received power at each light-sensor for three scenarios: empty test bed (first bar), test subject on the left-hand side close to the wall with the sensors affixed (middle bar) and that on the right-hand side away from the wall with sensors affixed (end bar) [32].

When the person is at the back right position, the opposite is true—sensors 6 and 7 are affected more than sensors 1 and 2.

The measured RSS values at each light-sensor are shown in Fig. 4. These plots show the change in the RSS with a test subject (a person of 1.8-m height) standing at each individual point on the grid. A very large dip can be seen on the top-left edge of each plot where the test subject stood immediately in front of the light-sensor causing a strong shadow. This shows the possibility of taking the RSS value from the same location on each plot to construct a fingerprint Identifier(ID) for that position. The proof of concept along with some preliminary results using that simple setup were reported in [32].

E. WKNN Classifier for Localization Using RSS

There are many classifiers to choose from when it comes to positioning that utilizes a fingerprint database. While classifiers like *Support Vector Machines* [35] and *Neural Networks* [36] have been extensively employed for indoor localization using wireless technology, they have not been commonly applied for VLP. The use of the WKNN [37] is another option to classify the online readings while employing an offline fingerprint database. The recently published research [17] has shown that WKNN is well suited for the active VLP system utilizing RSS. Therefore, for this work, the WKNN is applied to classify live RSS readings using the fingerprint database.

Let there be N light-sensors in the localization system. During the offline measurements, when the target is at a location (x_i, y_i), the corresponding ID for that location based on the RSS at the sensors can be defined as an $N \times 1$ vector

$$\underline{\mathbf{R}_i} = \left[\, R_{1,i}, R_{2,i} \quad \cdots, \quad R_{N,i} \,\right]^T. \tag{1}$$

Here, $R_{n,i}$ refers to the RSS at the nth light-sensor (dc level measured at the output of its trans-impedance amplifier) with the target being at location i with the coordinates (x_i, y_i). At the offline stage, RSS measurements are taken at all the sensors for M predefined locations and a $M \times N$ RSS fingerprint database is constructed. Now, the target can be localized in the live phase using the WKNN classifier.

During the live stage, the RSS vector at N light-sensors for a target at the location (x_j, y_j) is given by

$$\underline{\mathbf{R}_j^{\text{live}}} = \left[\, R_{1,j}^{\text{live}}, R_{2,j}^{\text{live}} \quad \cdots, \quad R_{N,j}^{\text{live}} \,\right]^T. \tag{2}$$

Here, $R_{n,j}^{\text{live}}$ is the RSS at the nth sensor during the live stage. The proximity of the live location to an offline location on the fingerprint database can be determined by computing the distance $d_{j,i}$ between the vectors $\underline{\mathbf{R}_j^{\text{live}}}$ and $\underline{\mathbf{R}_i}$. By sorting the distances in the ascending order, the "nearest neighbors" to the current live location in the offline fingerprint database are identified. The WKNN algorithm estimates the location of the target as the weighted average of the location of the first K-nearest neighbors as

$$\tilde{x_j} = \frac{\sum_{k=1}^{K} w_{j,k} \times x_k}{\sum_{k=1}^{K} w_{j,k}} \tag{3}$$

$$\tilde{y_j} = \frac{\sum_{k=1}^{K} w_{j,k} \times y_k}{\sum_{k=1}^{K} w_{j,k}}. \tag{4}$$

Here, $(\tilde{x_j}\tilde{y_j})$ is the estimated position of the target and (x_k, y_k) is the position of the kth neighbor. The weight $w_{j,k}$ is the reciprocal of the distance $d_{j,k}$, thus giving larger weights to nearer neighbors. The value of $K = 3$ was empirically chosen in the WKNN algorithm for the system, as it provided a good balance for optimizing both the median and maximum localization errors.

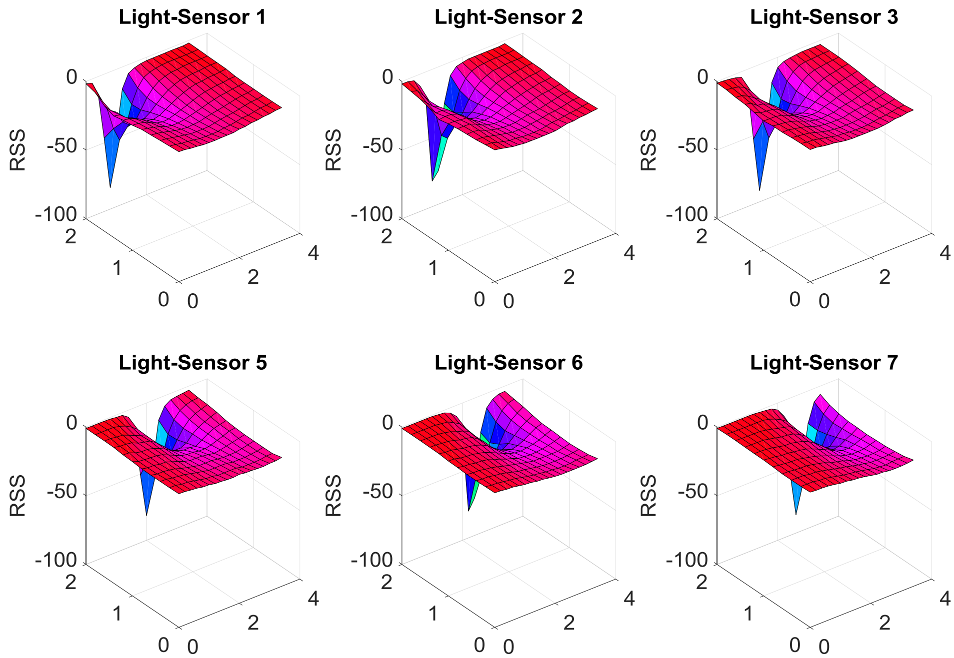


Fig. 4. RSS fingerprint at each light-sensor for the proof of concept setup. The *XY* plane represents the floor (units in m) [32].

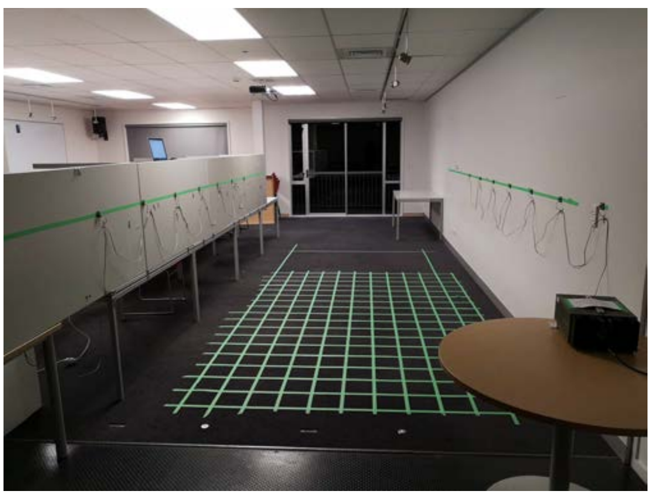


Fig. 5. Experimental setup showing the wall mounted light-sensors and the test space.

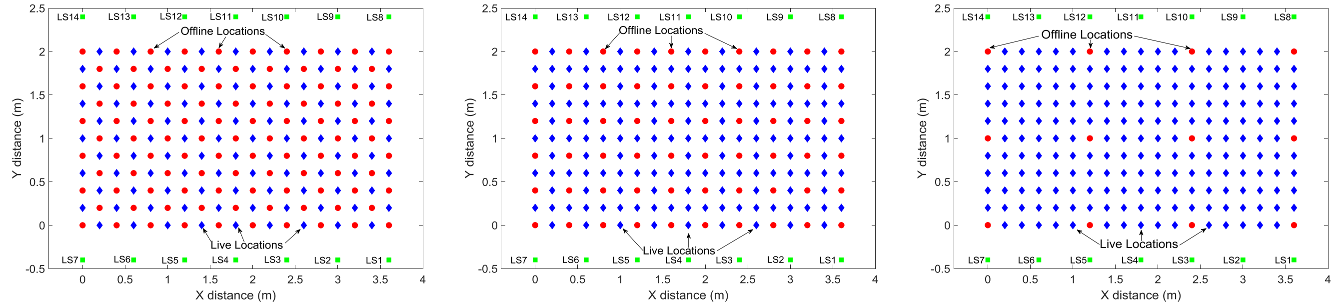
III. Localization Performance

This section investigates the localization performance of the system and reports the impact of various parameters on the localization accuracy.

A. Experimental Setup

The initial proof of concept setup described in Section II-C was found to have large positioning errors at the extremities of the test space. A slightly modified experimental setup was therefore used. The room was set up with 14 light-sensors (please see Section II-B for the description of the hardware). It was decided to place the sensors on two opposing walls (as opposed to only one wall described in the proof of concept setup). Also, the spacing of the light-sensors increased from 0.3 m (of the proof of concept setup) to an interval of 0.6 m. This was done to ensure that there were enough sensors near the ends of the test space. The physical setup can be seen in Fig. 5. Seven sensors were placed along each wall giving in total 14 sensing nodes [$N = 14$ in (1) and (2)]. A grid of 3.6 m $\times$ 2 m dimension with 0.2-m squares was marked out with the sensors being 0.4 m back from the grid on each side and in line with the end of the grid at both the ends of the experimental space. The width of the space was, therefore, 2.8 m and the length 3.6 m (however, with no walls across the ends). Data were collected at each grid intersection for a total of 209 locations using the acquisition method described in Section II-B. The data were split into two parts: 1) offline fingerprint database and 2) online RSS measurements.

All the experiments were conducted at night when the ambient light could be controlled. Multiple data sets were collected for the entire test space, as shown in Fig. 6. In each case, the data were collected starting at the first position located at the corner of the grid closest to light-sensor 7 (marked as LS7 in Fig. 6). A test subject then stood at each point on the grid in sequence while the reading was taken. Each reading consisted of taking measurements from each sensor simultaneously over a period of 5 s with the data being sampled 10 times per second, giving an array of 50 samples per sensor per reading. The readings were taken starting at (0, 0) and proceeding in the x-direction, i.e., (0, 0) to (1, 0), …, to (19, 0) before starting the readings in the next row. Each reading was taken for a 1.8-m tall human subject facing the wall, i.e., the line of the subject's shoulders was parallel to the wall. Readings were also taken with no test subjects being present (i.e., background reading representing effectively an empty room). Background readings were taken before and after each data set to verify that the ambient light level stayed constant.



(a) (b) (c)

Fig. 6. Experimental layout showing the location of the light-sensors and measurement locations for three different fingerprint databases. (a) Measurement locations-"Database 1". (b) Measurement locations-"Database 2". (c) Measurement locations-"Database 3".

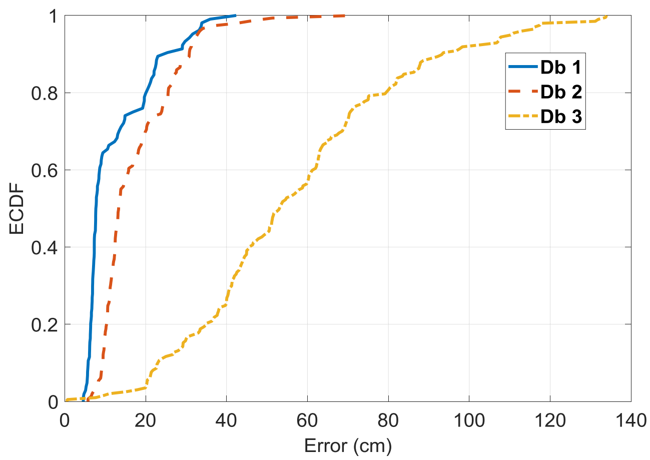


Fig. 7. ECDF of the localization error for three fingerprint database sizes.

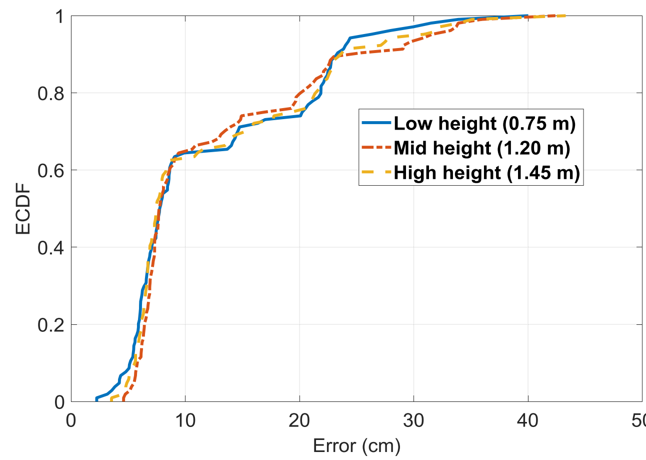


Fig. 8. ECDF of the localization error for three sensor heights.

TABLE II
MEDIAN AND 90-PERCENTILE ERRORS FOR DIFFERENT DATABASE SIZES

Error in cm					
Database 1		Database 2		Database 3	
Median	90-perc.	Median	90-perc.	Median	90-perc.
8	26	13	31	53	93

B. Impact of Fingerprint Database Size

Table II shows the median and 90-percentile localization errors for the three fingerprint databases of different sizes. Offline measurement locations can be seen in Fig. 6. The empirical cumulative distribution function (ECDF) of the localization error is shown in Fig. 7. It can be observed that there is a clear tradeoff between the localization accuracy and the size or resolution of the grid. The localization accuracy degrades as the fingerprint database becomes smaller with a sparser grid. The degradation of accuracy in going from Database 1 (111 offline measurements, $M = 111$) to Database 2 (60 offline measurements, $M = 60$) is relatively small. Also, for Database 3, with only 12 offline measurements, the 90-percentile localization error (93 cm) is still less than 1 m, thus making the WoW more accurate than many state-of-the-art wireless DFL systems [19].

It should be noted that the selection of the database is not optimized. The optimum fingerprint locations are dependent on many parameters with some being dynamic and also varying with the site. The offline measurement locations optimized for one test environment may not be ideal for another situation. Therefore, simple regular patterns for offline locations were utilized. The presented localization results could potentially be improved by using more favorable fingerprint databases found through the trial and error of various offline location sets. However, this can lead to an over-trained system. Besides, this may not be an objective representation of a real-world scenario, where it is not always feasible to optimize the location of the offline measurement or fingerprint locations.

C. Impact of Sensor Placement Height

Fig. 8 shows the impact on the localization accuracy of the sensor placement height on the wall. Three different heights were investigated with the light-sensors set at heights of 0.75, 1.2, and 1.45 m from the floor level. It can be observed that the height of the sensor placement does not have any noticeable impact on the localization accuracy of the WoW. Thus, the experimental results shown for the rest of this article are for the sensor placement height of 1.45 m.

TABLE III
DEFINITION OF DISTANCE METRICS

Distance Metric	Definition
Euclidean	$d_{j,i} = \sqrt{\sum_{n=1}^{N} \left(R_{n,j}^{live} - R_{n,i}\right)^2}$
Manhattan	$d_{j,i} = \sum_{n=1}^{N} \left\|R_{n,j}^{live} - R_{n,i}\right\|$
Canberra	$d_{j,i} = \sum_{n}^{N} \frac{\left\|R_{n,j}^{live} - R_{n,i}\right\|}{\left\|R_{n,j}^{live} + R_{n,i}\right\|}$

TABLE IV
LOCALIZATION ERRORS FOR VARIOUS DISTANCE METRICS

Error in cm (Database 1)					
Euclidean		Manhattan		Canberra	
Median	90-perc.	Median	90-perc.	Median	90-perc.
8	26	7	21	7	21

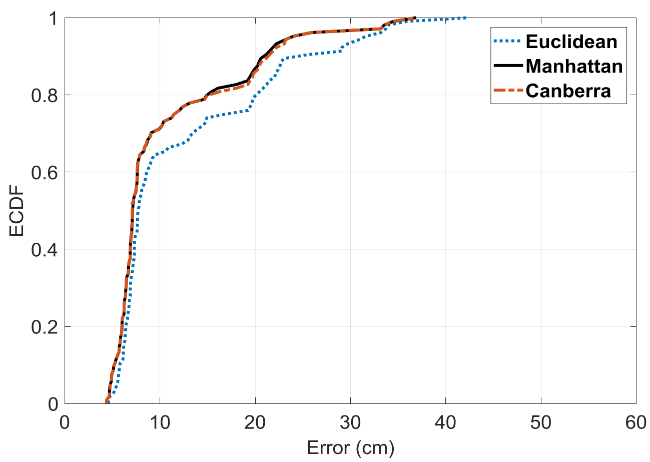


Fig. 9. ECDF of the localization error for various distance metrics.

D. Impact of Distance Metric

Euclidean distance is commonly utilized for identifying the nearest neighbors and computing the weight of the WKNN algorithm [37]. However, several alternative distance metrics are known from the literature [38]. A recent work on active VLP [17] has shown that the selection of the distance metrics can have an impact on the localization accuracy of the WKNN algorithm. Consequently, the effect of distance metrics on the accuracy of the VLP system was investigated. The distance metrics are defined in Table III. The localization results for Database 1 are shown in Fig. 9 and Table IV. It can be observed that the Euclidean distance is not the most accurate metric. Two other distance metrics (Manhattan and Canberra) produce lower localization errors. Localization results for Database 2 and Database 3 show similar trend.

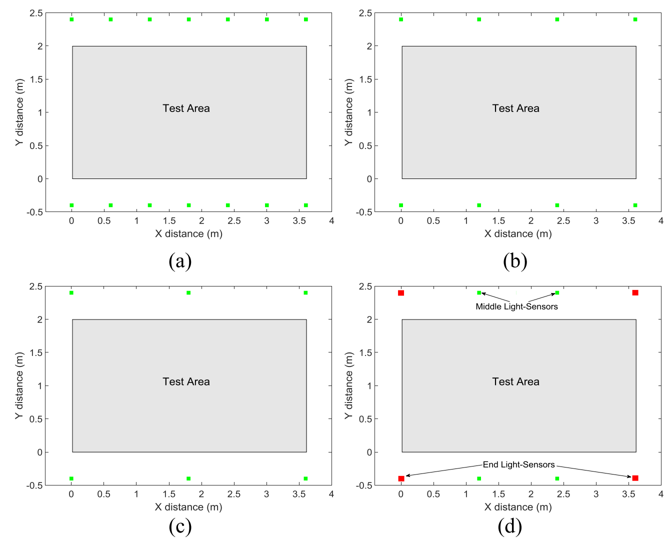


Fig. 10. Experimental layout showing the location of the light-sensors for varying sensor numbers. Note that two different layouts for the 4-sensor arrangements are shown in (d). (a) 14 Sensors. (b) 8 Sensors. (c) 6 Sensors. (d) 4 Sensors.

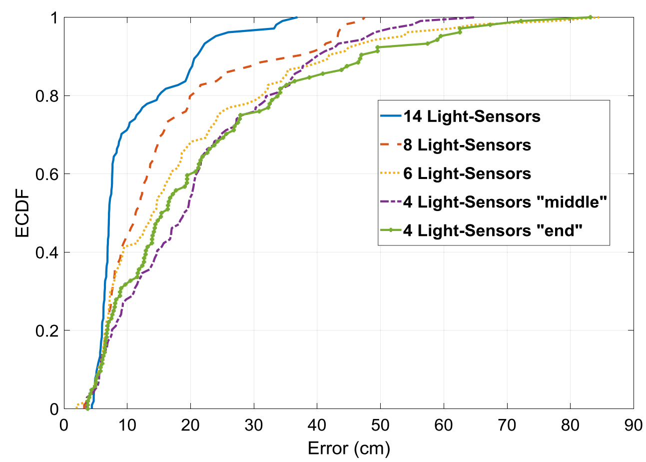


Fig. 11. ECDF of localization error for various number of light-sensors.

E. Impact of the Number of Sensors

The impact of the number of sensors on the localization accuracy of the WoW was also investigated. Fig. 10 shows the locations of the sensor nodes for these experiments. Fig. 11 and Table V show the localization performance for various number of sensors. As expected, the localization accuracy degraded when the number of deployed nodes was reduced. However, the 90-percentile error was below 50 cm, even with only four sensors being employed.

F. Tracking a Mobile Target

In order to test how the developed system tracks a moving target, multiple paths were followed by the test subject. The target walked along a marked path at a constant speed of 0.2 m/s. The steps were synchronized to a metronome to ensure that the distance covered by each step and the walking speed remained constant. The deliberate walking speed

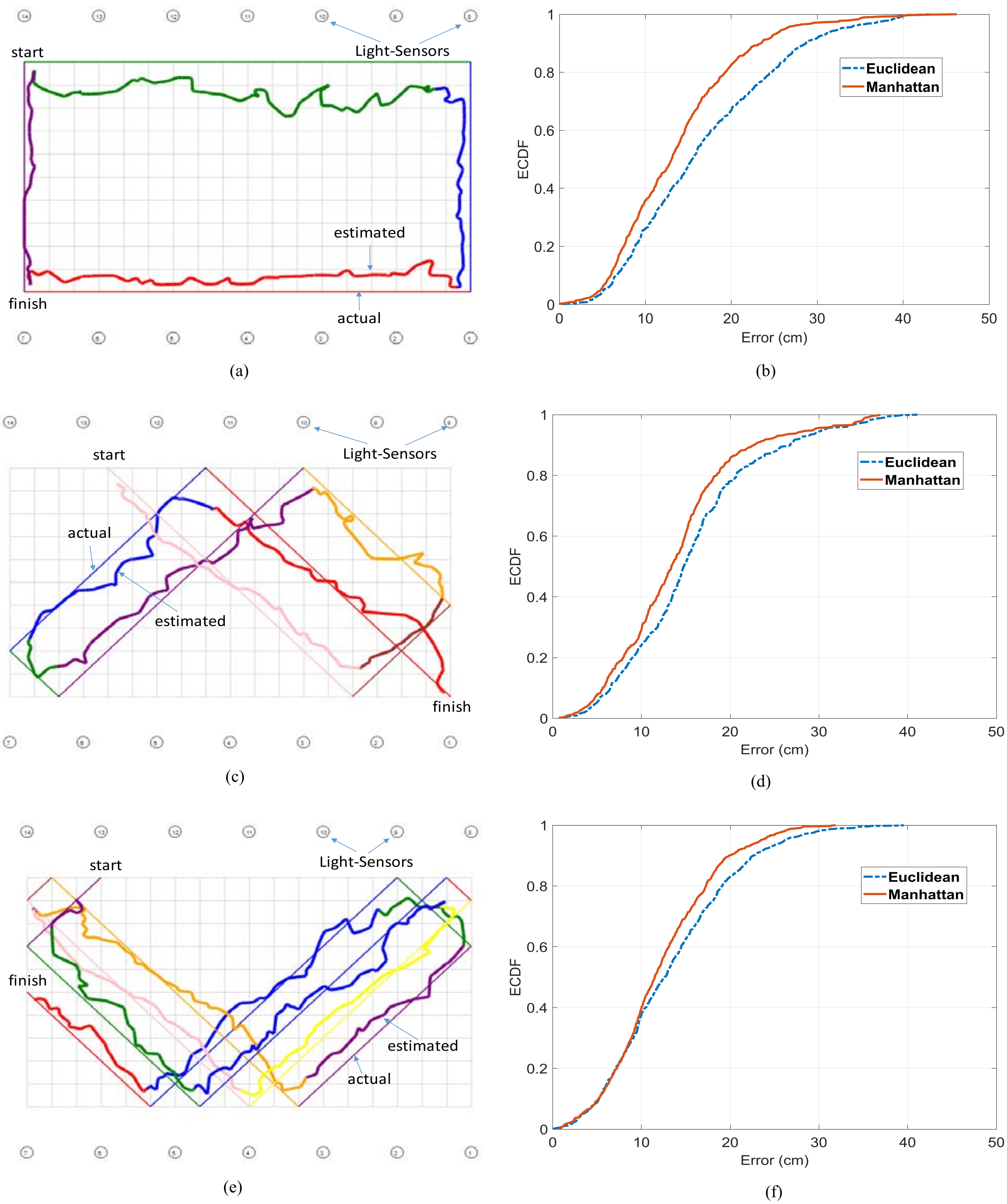


Fig. 12. Tracking performance for three different target routes. (a) Actual versus estimated route-Path1. (b) ECDF of the localization error-Path 1. (c) Actual versus estimated route-Path 2. (d) ECDF of the localization error-Path 2. (e) Actual versus estimated route-Path 3. (f) ECDF of the localization error-Path 3.

allowed the ground truth (the actual location of the target) to be accurately estimated. Each path was recorded over a 90-s period. Three different routes were employed to investigate the capability of the WoW in tracking a moving target. The results are shown in Fig. 12 and Table VI. It can be observed that the positioning error levels are similar for all three paths. In addition, the Euclidean distance performed worse among the three distances. The performances for the Canberra and Manhattan distances were nearly identical, and consequently only the results obtained for the Manhattan distance are shown against those of the Euclidean distance. When the subject walked around, the orientation of the subject varied, leading to changes in the size of the shadow. The fingerprinting was performed with the subject in a single orientation (facing one

TABLE V

LOCALIZATION ERRORS FOR DIFFERENT NUMBER OF LIGHT-SENSORS

Error in cm (Sensor height 1.45 m, Database 1), Manhattan Distance									
14 sensors		8 sensors		6 sensors		4 sensors (middle)		4 sensors (end)	
Median	90-perc.	Median	90-perc.	Median	90-perc.	Median	90-perc.	Median	90-perc.
7	21	11	38	14.5	42	19	41	16	47

TABLE VI

LOCALIZATION ERRORS FOR VARIOUS TARGET TRAJECTORIES

Error in cm											
Path 1				Path 2				Path 3			
Euclidean		Manhattan		Euclidean		Manhattan		Euclidean		Manhattan	
Median	90-perc.	Median	90-perc.	Median	90-perc.	Median	90-perc.	Median	90-perc.	Median	90-perc.
16	29	13	23	15	27	13	23	13	23	12	21

of the walls). Larger errors were observed when the subject was facing significantly different directions compared to those observed when the fingerprints were taken. This is more noticeable in Fig. 12(a). The positioning error is smaller on the left and right sides. Here, the test subject walked toward or away from the sensors with the body orientation being similar to that observed during the fingerprinting. Whereas for the top and bottom parts of the trajectory, the positioning error is more pronounced. For these trajectories, the orientation of the test subject is $\pm 90^\circ$ turned compared to that observed during the fingerprinting.

The sampling rate of the VLP system is 10 Hz, which is the maximum sampling frequency the custom-designed light-sensors can handle at the 16-bit resolution. The conducted experiments showed that the system could cope with a faster walking speed of up to 0.8 m/s. However, it was difficult to maintain a constant speed and achieve an accurate recording of the ground truth. Also, if the resolution is reduced, the sample rate of the current hardware can be increased allowing to track targets that are moving even faster. However, the loss of resolution would lead to a coarser estimation of the RSS and could potentially lower the localization accuracy. In future work, the hardware design may need to be improved to increase the sampling rate without sacrificing the resolution in order to track faster targets.

IV. CONCLUSION

This article presents the development and implementation of a passive visible light-based indoor localization system that employs cost-effective components. The system was able to position a target with a median error of 7 cm in stationary and 12 cm in mobile scenarios using 14 wall-mounted light-sensors. The VLP system performed effectively using the WKNN classifier and a fingerprint database consisting of 60 offline measurements within a 2 m $\times$ 3.6 m testbed. Weights computed using either the Manhattan or Canberra distance provided better positioning accuracy than the traditional Euclidean distance for the WKNN classifier. The placement of the light-sensors within a range between 0.75 and 1.45 m of height did not show any noticeable impact on the localization accuracy. Therefore, a sensor placement height of 1.45 m is preferable to reduce the possibility of occlusion resulting from furniture or other paraphernalia. The localization accuracy degraded once the number of light-sensors was reduced. However, even with only four wall-mounted sensors, it was possible to attain a median positioning accuracy of 16 cm for a stationary target.

Further work will expand the test to a full room-scale with the light-sensors embedded in all the room walls. In a larger room, enough shadows may not be cast by the target on the walls. In such a scenario, additional light-sensors may need to be embedded in the ceiling and the floor, in particular, in the middle of the room.

The experiments were undertaken at night. Therefore, changes in the level of ambient light were not investigated. The future work will study the quantification and mitigation of the impact of changing the ambient light. Ambient light is measured as a dc signal at the output of the light-sensors. The proposed VLP system infers the location through monitoring the change a target causes to the dc levels at various light-sensors. Therefore, a change in the ambient light level could affect the localization accuracy of the proposed system. This can potentially be mitigated by using VLC-enabled luminaires that transmit modulated light. Under such circumstances, the sensors will monitor the RSS at a specific set of frequencies rather than the dc levels. If the ambient light level changes, the RSS at the modulating frequencies will not change. The change in the RSS will be solely due to the occlusion, e.g., the presence of a target. Therefore, as long as the ambient light does not saturate the light-sensors, the accuracy of such a VLP system would not depend on variations in the ambient light. Another potential way to mitigate this could be to employ two separate RSS metrics measuring the long-term and short-term levels of the ambient light. A similar concept has been applied with RSS histograms for wireless DFL to offset the fluctuations of RSS occurring from the dynamic nature of the wireless channel [39].

The developed system was tested for a single target at a time, and as such, further investigation is planned to track multiple objects. Since generating the fingerprint database is a very time-consuming process, future research will look at the modeling of the RSS data, and their generation from a few strategically selected calibration points. Utilizing other types of classifiers (e.g., Neural Networks and Support Vector

Machines) and comparing their performance with WKNN will be another direction for future research. Finally, the effect of the color of the target's clothing on the system performance was also left for future investigation.

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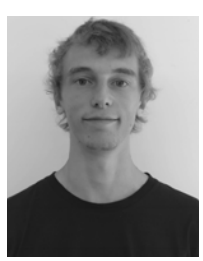

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