Foglight: Visible Light-enabled Indoor Localization System for Low-power IoT Devices

Shang Ma, Qiong Liu, and Phillip C.-Y. Sheu

***Abstract*—Advances in small and low power electronics have created new opportunities for the Internet of Things (IoT), leading to an explosion of physical objects being connected to the Internet. However, there still lacks an indoor localization solution that can answer the needs of various location-based IoT applications with desired simplicity, robustness, accuracy, and responsiveness. We introduce Foglight, a visible light enabled indoor localization system for IoT devices that relies on unique spatial encoding produced when mechanical mirrors inside a projector are flipped based on gray-coded binary images. Foglight employs simple off-the-shelf light sensors that can be easily coupled with existing IoT devices - such as thermometers, gas meters, or light switches - making their location discoverable. Our sensor unit is computation efficient; it can perform high-accuracy localization with minimum signal processing overhead, allowing any low-power IoT device on which it rests to be able to locate itself. Additionally, results from our evaluation reveal that Foglight can locate a target device with an average accuracy of 1.7 millimeters and average refresh rate of 84 Hz with minimal latency, 31.46 milliseconds on WiFi and 23.2 milliseconds on serial communication. Two example applications are developed to demonstrate possible scenarios as proof of concept. We also discuss limitations, how they could be overcome, and propose next steps.**

***Index Terms*—IoT, indoor localization, coded visible light, fog computing**

I. Introduction

Recent advances on the Internet of Things (IoT) as well as the importance that context-aware services have within the IoT world help people realize the significance of indoor positioning for these IoT devices in many application scenarios. However, *classical* positioning technology based on wireless radio signals is still shy of its potential to provide truly ubiquitous and real-time location for many IoT applications [1] [2]. Although radio technologies offer a great opportunity to measure internode distance and bearing or to perform simultaneous angle-distance measurements by utilizing heterogeneous radio interfaces, wireless localization systems are still inaccurate and unreliable in indoor environments. This unreliability is primarily caused by three major challenges, namely, *multipath reflections* [3], *environmental dynamics* [4], and *device heterogeneity* [5].

As a matter of fact, researchers and developers often face more challenges while developing indoor localization systems for IoT applications. Many IoT devices are battery-powered and have limited computation power and storage capability, whereas many IoT applications have high demands on accurate and real-time location information and are inherently intolerant to small localization errors and system latency. These needs motivate fog computing, which has the potential to offer location-based services that deliver better delay performance and user experience. As our grocery store and museum applications demonstrate later, if a localization scheme incorrectly places a customer in the adjacent aisle in the store, downloads information about the adjacent painting onto a visitor's mobile phone, or performs the above actions with undesirable delay, the purpose of localization is entirely defeated. Consequently, we prefer the system to be *high-accuracy*, *low-latency*, and have only *minimum computation overhead.* This pushes us into using wireless signals, such as visible light or Ultra-wideband (UWB) [6] signals, rather than, for example, WiFi [7] and Bluetooth [8]. Even in the homes and workplaces where we *could* deploy more and more computing infrastructure, the cost, high power consumption, and low reliability for traditional radio signals are often prohibitive.

In this paper, we consider a new indoor localization technique that allows low-power IoT devices to locate themselves with sub-centimeter accuracy, low signal processing overhead (*thus low latency*), and minimum power consumption. This *Foglight* technique operates by projecting a sequence of gray-coded binary images into the environment, which uniquely encodes each pixel inside the projection area with a pair of coordinates $<x, y>$. A particular IoT device can locate itself by collecting and decoding a sequence of light intensity at a given place using an off-the-shelf light sensor. This sensor is simple and inexpensive, which allows it to be easily incorporated into many existing IoT devices, thus enabling them to recognize their own position inside the projection area. Additionally, the procedure required to restore a device's position from sensed light is fast (11.75

This paragraph of the first footnote will contain the date on which you submitted your paper for review. It will also contain support information, including sponsor and financial support acknowledgment. For example, "This work was supported in part by the U.S. Department of Commerce under Grant BS123456".

S. Ma is with the Department of Electrical Engineering and Computer Science, University of California, Irvine, CA 92697 USA (e-mail: shangm@uci.edu).

Q. Liu is with the Fuji Xerox Palo Alto Laboratory, Palo Alto, CA 94304 USA (e-mail: liu@fxpal.com).

P. Sheu is with the Department of Electrical Engineering and Computer Science, University of California, Irvine, CA 92697 USA (e-mail: psheu@uci.edu).

milliseconds) and power efficient, so they can be applied to battery-powered devices and deployed for large-scale applications over a long period of time. Further, Foglight realizes fine-grained localization with sub-centimeter precision. This opens a huge field of new applications where high-accuracy location information of IoT devices is demanded. Finally, our experiments show the proposed approach is feasible. In a controlled lab study, Foglight can offer real-time localization services with 1.7 millimeters of accuracy across a variety of environments. We also provide two examples in section VI as proof of concept.

This paper is organized as follows: Related work is provided in section II. Section III presents an overview of the sensing technique used in Foglight. Section IV depicts the technical details of four key components in our prototype implementation. We provide an experimental validation and performance evaluation of the proposed system conducted in a typical indoor office setting in section V. Two example applications of the current system and future works will be explored in section VI and VII, respectively. Finally, we conclude our investigation in section VIII.

II. Related Work

A. *Conventional Radio Technology Based Approaches*

A wide range of technologies have been explored for indoor positioning purposes for over a decade. The most well-known approaches are those based on traditional radio signals, such as WiFi [9][10], ZigBee [11][12], Cellular Network [13], Bluetooth [8][14], FM radio [15][16], and RFID [17][18]. With these wireless technologies, the location of a target in the environment can be estimated by measuring one or more properties of the electromagnetic wave radiated by transmitters and received by the target. So far, three localization techniques have been extensively investigated: Angle of Arrival (AoA), Time of Arrival (ToA) or Time Difference of Arrival (TDoA), and Radio Signal Strength (RSS) fingerprinting.

More specifically, AoA-based measurements take advantage of either antenna arrays or directional antennas to obtain the orientation information of a target relative to multiple reference nodes and then determine its position from the intersection of lines [10][19]. However, special antenna designs are expected for such systems, which increases the complexity and cost of real-world deployment and prevents them from ubiquitous utilization. ToA/TDoA solutions estimate distances from the propagation time of a radio frequency (RF) wave between transmitters and receivers [20][21]. These approaches rely on proper propagation models for the wireless signals and precise timing measurement to obtain accurate distance information. However, the success of modeling wireless signal propagation indoors is limited due to highly unpredictable shadowing, reflection, refraction, and absorption from the interplay between signals and the environment [22].

The most widely adopted design is wireless fingerprinting [9]. Wireless fingerprinting usually contains two phases, an offline training phase and an online positioning phase. In the first phase, a site survey is conducted when certain properties of the underlying wireless signal (e.g. RSS of WiFi or Bluetooth) are recorded at selected locations in the area of interest, resulting in a so-called *radio map*. In the positioning phase, a target to be located samples its signal fingerprint and *searches* the radio map to estimate its current location. Both deterministic methods such as RADAR [23] and probabilistic methods such as Horus [24] have been employed for location estimation in previous work. However, RSS is not a reliable estimator because it is susceptible to indoor multipath reflection and shadowing. Consequently these solutions can only provide low to medium accuracy, typically to a few meters [23][25].

B. *UWB Based Approaches*

More recently, systems based on UWB technology have become increasingly popular for indoor localization applications. What makes this technology feasible for such applications is the modulation scheme of UWB signals [26].

In a typical UWB-based system, data is transmitted through very narrow pulses (*e.g.* nano or sub-nanosecond pulses) spreading over a band of hundreds of megahertz [27]. In particular, this design gives two advantages to indoor localization systems. On the one hand, such short pulses offer sub-nanosecond accuracy for timing measurement of the received UWB signal, which corresponds to centimeter-level accuracy in distance. Further, it increases the robustness of the overall system against multipath fading [28], which is still a challenging problem for conventional radio signals due to signal reflection in indoor environments.

Although UWB technology possesses desirable properties for accurate ranging and positioning [29], it is not a universal solution. For one thing, UWB communication has relatively low effective range due to the need of operation in unlicensed 3.1-10.6 GHz bands and the transmit power restriction [30]. This suggests that a sufficient amount of reference nodes will be needed for large-scale deployment and these nodes should be affordable. For another, UWB receivers are power-hungry, which makes it unsuitable for low-power IoT applications [31].

C. *Light Based Approaches*

Previous systems that employed light to determine indoor position include [32]-[37]. For these systems, high precision localization schemes often required well-shaped LEDs for propagation modeling [35][36][37] or ultra-dense deployment [36] (multiple LEDs within the camera's field-of-view). In contrast, Foglight features an easy-to-deploy approach in which off-the-shelf Digital Light Processing (DLP) projectors and light sensors are used to provide high-resolution localization. Since projecting binary images into the environment is the inbuilt function of the projector, Foglight does not require any augmentation of the projector itself. Although we only use one DLP projector in our current implementation, we will leave how multiple projectors can be stitched together to provide large-scale localization as a future step.

D. *Other Related Work*

In the context of indoor localization for IoT services, there exist several approaches to provide indoor location for IoT devices. More specifically, Zou et al. [38] applied an online sequential extreme learning machine based indoor localization algorithm on WiFi signals so that the proposed system reduced the time consumption and manpower cost for an offline site survey in traditional fingerprinting-based wireless signal indoor localization systems. Wu et al. [39] proposed a genetic algorithm based localization scheme to estimate the location of unknown RFID nodes, given that RFID technology has been used in a variety of IoT applications. Alletto et al. [40] placed Bluetooth Low Energy (BLE) beacons in different rooms of a museum as wireless landmarks. An application running on the user's mobile device is used to determine the user's location based on the value of Received Signal Strength Indicator (RSSI) so that personalized cultural content can be provided to visitors.

In this work, we advocate an encoded projection based localization system with the focus on low-power IoT devices featuring limited power consumption, communication capability, and computation resources. To the authors' best knowledge, this is the first time that projection-based encoded light signal is exploited as an indoor localization method to obtain fine-grained, real-time location data for such devices. A performance comparison between the proposed system and state-of-the-art existing work is given in Table II.

III. System Design And Implementation

Foglight takes advantage of particular properties of DLP projectors in order to assign unique coordinates to each pixel inside the projection area. Foremost, a DLP projector normally has a Digital Micromirror Device (DMD) chip, which consists of millions of micro optical mirrors arranged with a diamond pixel array geometry and configuration. These micro mirrors can be flipped between two states (*on* and *off*) independently at a high frequency. This fast-flipping property allows it to be used to modulate light by changing projected images.

Another important property that is exploited is a sequence of gray-coded binary patterns can be used to encode the projection area by assigning a unique pair of coordinates to each pixel in it. So, while projecting a sequence of gray-code patterns by flipping the corresponding mirrors inside the projector, the light signals coming out of each mirror unambiguously transmit its pixel coordinates on the projector plane into the environment. These two properties work in concert to enable Foglight to provide fine-grained location information to IoT devices simply but reliably.

To capture light intensity at different locations, we use an off-the-shelf light sensor, TAOS TSL13T. This sensor is particularly well suited to locate IoT devices, which are normally low-cost, battery-operated, and have limited computation resources. If mass-produced, this sensor and its required peripheral circuit might cost less than two dollars.

Our system architecture (Fig. 1) illustrates the building blocks discussed above and demonstrates how they work seamlessly to deliver an indoor localization system for fine-grained device tracking. Our method has one important constraint shared by all existing visible light-based indoor localization systems: it can only locate devices inside the projection area, or rather it has a line-of-sight requirement. This condition needs to be met not only because we use visible light to convey localization information, but also because we envision the projector to be integrated with existing lighting fixtures in the environment, providing both location discovery and smart environment illumination *simultaneously*.

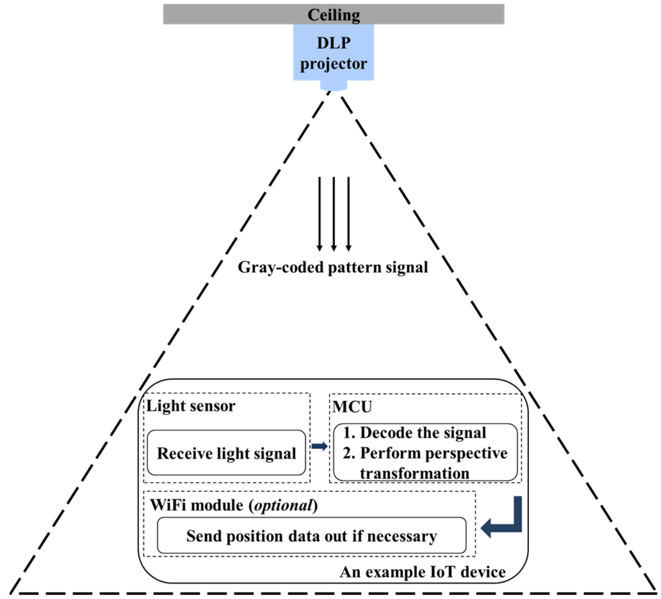


Fig. 1. System architecture of Foglight. The dashed triangle represents the projection space.

Sensing in Foglight is surprisingly robust in a wide variety of use contexts. The same sensing technique can be used for TV controllers, mobile robots [41], rice cookers, temperature controllers, and many other low-power IoT devices. The only notable restriction is that these devices must be *seen* by the projected light, thus blocking the light will prevent the device from locating itself. So, for example, a smart shopping cart augmented with our sensor could be used for customer behavior tracking, but if the sensor is covered by a shopping item, the cart is not likely to locate itself inside the shop. However, this is not necessarily a negative quality. If customers are selecting personal products, they might not want to be tracked by the system. A good example of this is the pharmacy area in a retail store, where shoppers would like to protect their privacy about which products they are viewing and purchasing.

IV. Location Discovery

A. *Gray-coded Position Encoding*

Foglight is based on the projection of a set of patterns onto the desired environment, such as walls, tables, and much more. These patterns are specially designed so that each pixel inside the projection area has its own codeword (a sequence of binary digits), and there is a direct mapping from the assigned codeword to the corresponding coordinates of the pixel on the projected pattern. Codewords are simply numbers, which can be mapped in the pattern by using gray levels, colors, or geometrical representations.

We adopted an easy but robust coding strategy called gray code [42], which is one of the common time-multiplexing pattern projection techniques. In this case, a set of patterns is successively projected onto the surface. The codeword for a given pixel is formed by the sequence of illuminance values for that pixel across the projected patterns along time. The advantage of this design is that the structure of each pattern can be very simple, which simplifies the procedure for decoding the coordinates from the codeword.

In Foglight, only two illumination levels are used, which are coded as 0 (*black*) and 1 (*white*). Each pixel has its own codeword formed by a sequence of 0s and 1s that correspond to its value in each projected pattern. Thus, a codeword is obtained once the sequence is completed. This design helps Foglight achieve high accuracy for localization due to three factors. First, since multiple patterns are projected, the codeword basis tends to be small (two in Foglight) and only a small set of primitives (0 and 1) are used, which are easily distinguishable from each other. Second, a coarse-to-fine paradigm is followed, meaning the position of a pixel is being encoded more precisely while the patterns are successively projected. Finally, an important advantage of gray code is that consecutive codewords have a Hamming distance of 1, meaning it is more robust against noise. Fig. 2 demonstrates an example in which three vertical (Fig. 2 left three) and three horizontal patterns (Fig. 2 right three) are used to resolve an 8×8 unit grid.

B. *Embedded Synchronization Signal with High Reliability*

Foglight can be used in a variety of indoor environments. More specifically, we use Manchester coding [43] to transmit the data patterns through a visible light channel to remove the dependency on the dc voltage of the received light intensity, which can be influenced severely by ambient lighting conditions. This scheme improves the signal-to-noise ratio of the overall system. Further, Foglight does not require any additional communication channel for synchronization but instead has embedded synchronization frames inside each data package, allowing the sensor units to be synchronized with the data source automatically.

This encoding scheme also helps with the flickering issue of visible light communication. This is usually due to long runs of 0s or 1s and may cause serious detrimental physiological changes in humans if the fluctuation in the brightness of the light is perceivable to human eyes [44]. In Foglight, each 1 or 0 is followed by its reverse bit (except the header, which has three 1s in a row), and the number of 1s in each packet is only one more than the number of 0s. This design keeps switching between 1 and 0, freeing the system from fluctuation so that users always see the projector as a stable light source.

Fig. 2. An example of gray code images for an 8×8 grid.

C. *Signal Detection & Position Reconstruction*

The sensor unit in Foglight includes one or two light sensors to decode light signals. The number of light sensors on a single sensor unit depends on the target application, as detailed later. Each light sensor is connected via a signal conditioning circuit to the same Arduino Micro microcontroller, using its general digital I/O port. The microcontroller is an Atmel Atmega32U4 chip running at 16 MHz and contains 26 general digital I/O ports, each of which can be used to collect light intensity by configuring it for input and evaluating the voltage level. The signal conditioning circuit contains an amplifier and voltage comparator, which not only increases the signal strength even when the sensor unit is far away from the projector, but also removes unwanted small signals (*noise*). In our prototype implementation, the sensor unit can detect the projector's location signals from up to 4.5 meters. Finally, the firmware running on the microcontroller collects light signals every 250 microseconds and restores the original position data, which can then be sent out to a host PC for event triggering and data logging via a WiFi module. We use a RN-XV WiFly module from Sparkfun in our current setup.

D. *Projector-Light Sensor Homography*

Foglight is designed to provide fine-grained 2D physical coordinates for low-power IoT devices with high accuracy. In attempting to answer this challenge, another key component in the system is projector-light sensor calibration.

To obtain the physical coordinates of the sensor unit, the position, orientation, and optical parameters of the projector relative to the interaction surface should be known. Consider that there exists a point (x', y') in the projector plane, that, in our case, is a pixel on the DMD mirror array inside the projector, and it is projected to a point on a projection screen, for instance, a flat table, with physical coordinates (x, y). (Here, we assume that the origin on the table is already known.) The relationship between (x', y') and (x, y) is determined by a planar projective transformation whose parameters further depend on the position and orientation of the projector relative to the table, and the optical parameters of the lens inside the projector. This relationship is also known as the homography between the pixel coordinates on the projector plane and the Euclidean coordinates in the physical space.

In Foglight, (x', y') coordinates can be observed and decoded by a light sensor and (x, y) can be measured relative to a user-defined origin. Therefore, H can be calculated with the following steps: (1) marking a certain number of points in the projection area; (2) measuring the distances between these points and the origin of the physical plane; and (3) collecting the pixel coordinates of these points using a light sensor. The inbuilt *findHomography* function [45] in OpenCV is used to find this transformation matrix, which will be applied to future sensor readings to obtain the Euclidean coordinates of a projected point in Foglight. We have followed these steps to calculate the homography in our experiments. We evaluate the performance of this design relative to localization accuracy in the next section.

V. System Evaluation

To assess the feasibility of our localization approach, we created a proof-of-concept system seen in Fig. 3. For evaluating the different features of our Foglight localization technique, a comprehensive evaluation was conducted. These experiments are used to evaluate the following features of this proposed system.

- Localization Latency
- Localization Refresh Rate
- Localization Accuracy
- Ambient Light Robustness

Different types of experiments have been designed to examine these features respectively. All these experiments are conducted indoors. During the evaluation, a DLP projector was installed behind the ceiling (Fig. 3), and a flat office table was used as an interaction space. The distance between the projector and the office table is 2 meters, and the resulting projection area is 1380 mm × 860 mm.

A. Localization Latency

The first fundamental question that we aim to answer in this paper is: *can we use Foglight for real-time location-based IoT applications and services*? We should note that the latency of Foglight comes from multiple levels. Foremost, the visible light packet itself is 47 frames in our current implementation, and 250 microseconds for each frame. This is 11.75 milliseconds long in total. Further, the microcontroller adds a certain delay while decoding the collected light intensity, restoring the original physical coordinates, and then packing position data for transmission. Finally, to make Foglight portable and compatible with existing mobile devices, such as user's mobile phones, we chose WiFi for communication between Foglight and target devices in our evaluation. Open Sound Control (OSC) [46] is also used as the data transmission protocol because of its simplicity and robustness. The WiFi connection is the communication bottleneck of our current implementation because the WiFi bandwidth is shared between the Arduino board in Foglight with other devices in the testing environment, including desktops, laptops, mobile phones, and a variety of other wireless devices. Therefore, we designed the following experiment to measure the latency of the proposed system.

1) Experiment Design

We used a simple setup to measure the delay between the time when Foglight receives a "start" command for position decoding and the time when a laptop (2.2 GHz CPU, 8 GB memory) receives the decoded position through a WiFi connection and applies the homography to the sensor readings to get the final position. Fig. 4 demonstrates our setup for this experiment. A program is developed to record a timestamp of a keypress event from the keyboard. Whenever the user presses the "space" key on the keyboard, the corresponding timestamp is recorded by the program, which also notifies Foglight to start the position detection process through serial communication running at 115200 baud. In turn, Foglight will send the detected position data to the same laptop through WiFi connection once it finishes data processing. The time interval between this program detecting the keyboard event and it receiving a position package is considered as system latency.

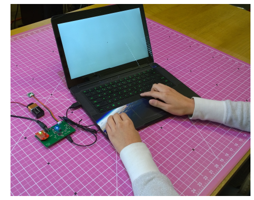


Fig. 4. Experiment setup to evaluate system latency of Foglight.

2) Results

Our evaluation consisted of two phases. First, we transmitted location data from the sensor unit to the host PC using a WiFi connection. We then ran the second phase of this experiment by repeating this process, but this time we used serial communication to send the position data collected by Foglight to the host PC. Six participants were recruited from our lab to collect 1200 groups of time difference measurements, and an average latency of 31.46 milliseconds was reported when using the WiFi connection. The delay decreases to 23.2 milliseconds when serial communication (115200 baud) is used.

B. Localization Refresh Rate

The second research question we would like to answer in this paper is: *does Foglight support mobility*? An important feature of IoT, especially within the Fog Computing paradigm, is that objects equipped with sensors could be moving all the time. Therefore, *service continuity* should be supported in various scenarios. At the localization level, the refresh rate of Foglight plays an important role to ensure location-based services are available at all times. The same six participants were invited for the following evaluation to find out the number of positions that Foglight can detect at different movement speeds.

1) Experiment Design

Fig. 5 demonstrates the setup of this evaluation, and the

Fig. 3. Left: (1) Light sensors, (2) Microcontroller, (3) Battery, (4) WiFi module in Foglight; Middle: A DLP projector installed on the ceiling; Right: The DLP projector for pattern projection.

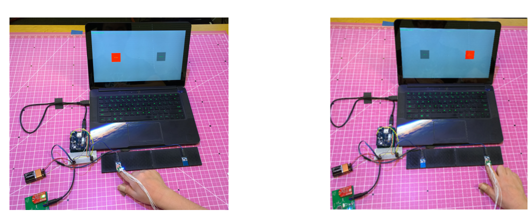


Fig. 5. Experiment setup to evaluate localization refresh rate in Foglight. Left: the user touched the left pad; Right: the user touched the right pad.

procedure to conduct this experiment is detailed as followed. All six participants were asked to situate a sensor unit on one of their fingers and touch two touchpads [47] in a fixed order (left first, then right). They were also asked to perform this action at different speeds: *normal*, *medium*, and *as fast as possible*. The time when these two touch sensors are activated were used as timestamps indicating the beginning and end of a single test, and the time difference of clicking these two pads consecutively and the physical distance between them were used to calculate the movement speed of users' fingers. To make our experiment as accurate as possible, the participants were given a demonstration of the system first before being allowed to practice with it. Once they were familiar with the procedure, we started the experiment.

The distance between these two pads is 20 centimeters. This distance is chosen to be long enough so that participants must move their fingers for a measurable period of time, but not so long that they have to move or stretch their body to access the second touchpad, which obviously will decrease their movement speed and affect the experiment accuracy. The time interval between two touch events is detected by another microcontroller (Arduino Uno) and sent to the laptop through serial communication (115200 baud) for data logging. A program running on the same laptop is used to count the number of position packages during this time interval.

We repeated the above set of experiments 10 times for each speed case. Participants were allowed to use any finger for the touch action, but required to use the same one during a single test. Thirty tests were performed for each user, totaling 180 tests for all six participants. Participants were allowed to take a rest and change to another finger between the tests.

2) *Results*

Fig. 6 illustrates the tracking performance of Foglight with different moving time, varying among 955.504 milliseconds, 547.692 milliseconds, and 435.105 milliseconds, respectively. Fig. 6 also shows average movement speeds 211 mm/s, 368 mm/s, and 461 mm/s, and the average number of position packages received at these three different speeds is 84.96, 84.955, and 84.937. Each package contains the position data sensed by the sensor unit on the user's finger. This agrees with the theoretical maximum refresh rate of Foglight, which is 85.1 Hz and decided by the total number of patterns the projector can

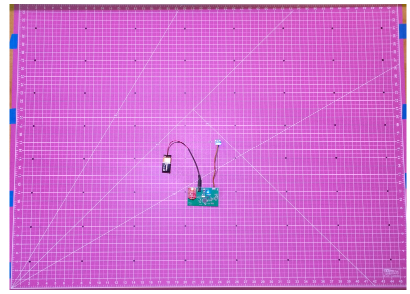


Fig. 7. A test arena for calculating the homography.

send every second and the length of a position packet. This quantity can be calculated by this equation:

$$r = \frac{4000(\textit{total number of patterns per second})}{47(\textit{number of patterns for a single position})} \approx 85.1 \quad (1)$$

This setup simulated a scenario where IoT devices have spatial movement while sensing and collecting information. Our findings underscore that Foglight can maintain a high refresh rate even when the target devices are moving at a high speed, indicating that our proposed localization technique can meet this challenge and provide continuous location-based services without disconnection.

C. *Localization Accuracy*

1) *Experiment Design*

To evaluate the localization accuracy of our proposed system, a test arena was developed. A commercial cutting mat with grid markers was placed on the table to provide ground truth data. The size of the cutting mat itself is 36"× 48" and the grids on top of it are located at a 0.5" distance.

As shown in Fig. 7, 64 points (black dots marked on the mat) were chosen for data collecting, and they were selected to be uniformly distributed in the projection area. A sensor unit was placed at all these points to collect pixel coordinates on the projection plane, and their physical distances regarding the center were also measured. The homography under this setup was calculated based on these two sets of data. We also collected the pixel coordinates of another 56 points, which are different from the 64 points from the first step, and applied the

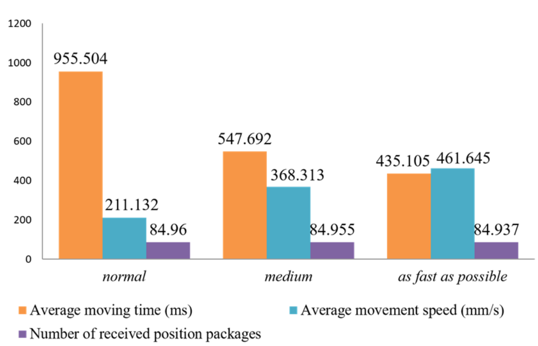


Fig. 6. Tracking refresh rate of Foglight at different movement speeds.

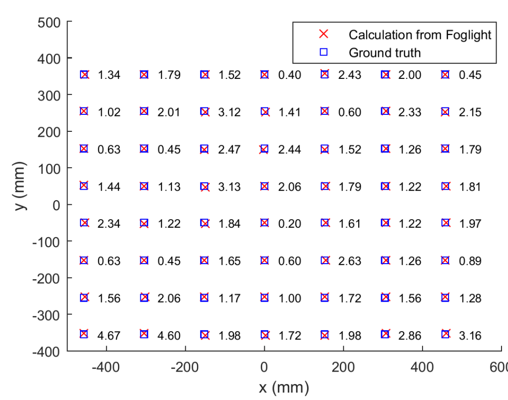


Fig. 8. Localization errors of all 56 points.

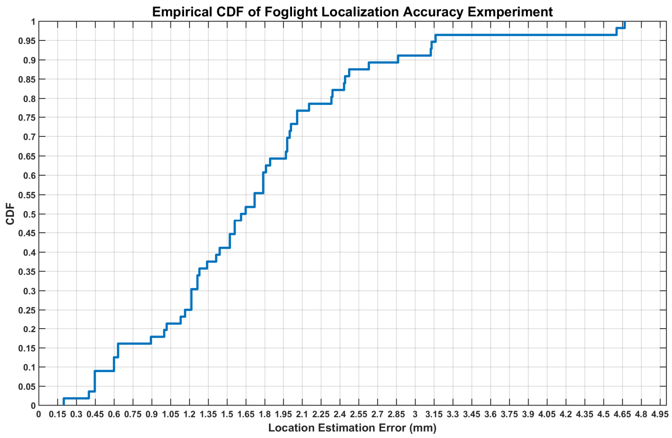


Fig. 9. The empirical cumulative distribution function of localization error for 56 points inside the projection area.

homography to them. The physical coordinates of these 56 points were also measured as ground truth. The difference between the ground truth and the calculation from Foglight for these new 56 points shows the localization error. These errors are plotted for better understanding.

2) Results

A 2-D plot (Fig. 8) shows how much of the errors are at different locations inside the projection area. The error is defined as the Euclidean distance between the computed coordinates from Foglight and the ground truth. It is clear from this figure that the errors are small and the accuracy is high. For the whole projection space, Foglight achieved an average error of 1.707 millimeters and the standard deviation is 0.918 millimeters. The empirical cumulative distribution function (CDF) for this experiment is also shown in Fig. 9 and it can be seen that for 95 percent of the selected evaluation points, Foglight has a localization deviation of less than 3.15 millimeters. This demonstrates that Foglight meets its goal of sub-centimeter device localization in practice.

D. *Ambient Light Robustness*

Since Foglight is visible light driven, we investigated its behavior and robustness with respect to ambient light across different lighting conditions. We placed a sensor unit at a known place inside the projection area and collected the restored positions generated by Foglight, as shown in Fig. 10. We also measured the ambient light intensity around this sensor unit by resting a light meter next to it. The metric used here to quantify the system reliability is the percentage of correct readings generated by Foglight.

As shown in Table I, we collected eight groups of sensor readings, generating a total of 8000 positions. The first column indicates different light intensity in the environment. Since the proposed system is driven by a visible light projector, the projector itself will increase the light intensity of the projection area by a certain range. Thus, the second column in the table illustrates the light intensity of the projection space after the projector is turned on. The third column logs the result from this experiment, showing the percentage of accurate position readings at different lighting setups. This experiment revealed that our localization technique can work reliably when the ambient light level is less than 345 Lux. However, if the environment is brighter than this threshold, Foglight fails to work properly. We will explore how to solve this problem in section VII.

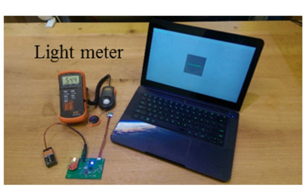


Fig. 10. Experiment setup to evaluate system robustness under different lighting conditions.

TABLE I. LOCALIZATION ACCURACY UNDER DIFFERENT CONDITIONS

Ambient Light Intensity (Lux)	Ambient Light + Foglight Intensity (Lux)	Accuracy Percentage (%)
232	384	100
312	444	100
336	464	98.7
345	472	94.4
349	482	22
355	487	0
400	538	0
483	614	0

E. *Comparison with Other Localization Systems*

Finally, we also compared the experiment results obtained by our prototype implementation to those from state-of-art systems in the literature. Note that the way indoor localization systems are evaluated and compared can be rather tricky. Previous studies have shown that a plethora of factors may affect the performance of a particular indoor positioning technology during system evaluation [4], such as setup of evaluation environment, evaluation points selected in a given environment, and the amount of time that has been devoted to developing the system under investigation. Since the goal of this work is to promote high-accuracy, low-latency indoor localization technology for low-power IoT devices, we propose the following evaluation criteria for this type of scenario: *accuracy*, *precision*, and *hardware complexity*.

Accuracy is arguably the most important requirement for positioning systems. Specifically, *mean distance error*, which represents the average Euclidean distance between the true and reported coordinates of selected evaluation points, has been adopted as a performance metric by many existing studies. One good example is the Microsoft Indoor Localization Competition 2014-2017 [26], where more than 100 teams from both academia and industry working on indoor localization technology have been invited to deploy their systems in realistic, unfamiliar environments and compete with each other in terms of accuracy.

As those who are familiar with positioning systems will recognize, however, it is not enough to measure the performance of a positioning technique only by observing its

TABLE II. COMPARISONS WITH REPRESENTATIVE SYSTEMS

Reference	Technical Approach	Accuracy	Precision	Mobile Node Complexity	Infrastructure Complexity
Dahlgen and Mahmmod [14]	BLE RSSI Trilateration + Particle filter	2.337m	28.2% within 2m; 92.5% within 4m	A cellphone supporting BLE	Ten BLE modules within 88 m^2
Beder and Klepal [25]	WiFi fingerprinting + Bayesian filter	1.56m	Unspecified	WiFi connection and signal strength measurement	2D floor map, ten access points within 300 m^2, a backend server
Shimosaka *et al.* [11]	ZigBee fingerprinting	1.5m	95% within 3.38m	A MCU and a ZigBee module	Six ZigBee modules within an area of 63.22 m^2
Hammer *et al.* [48]	Sound ToF	1.22m	80% within 1.1m; 90% within 2.4m	A microphone, a RF transceiver, and a DSP computation unit	Six loudspeakers, a backend PC, a RF transceiver
Quantitec Intranav [29]	UWB TDoA	0.168m	60% within 0.14m; 90% within 0.31m	A UWB transceiver	Eight UWB anchors within 600 m^2 and a cloud server
Xie *et al.* [34]	Spatially coded infrared LED	0.041m	95% within 0.092m	A light sensor, a MCU, and a wireless link (*optional*)	An infrared LED, a customized lamp shade, a step motor, and a MCU
The Proposed Foglight	Encoded visible light	0.0017m	95% within 0.00315m	A light sensor, a MCU, and a wireless link (*optional*)	A DLP projector

accuracy. To be more specific, the reported coordinate is basically an estimate, which heavily depends on the sample size considered in the evaluation. A few data points that represent inevitable, occasional failures of a localization system can overly influence the *mean distance error* value. Therefore, we also reported a measure of precision, which demonstrates how consistently a particular system works. In other words, it is a measure of the robustness of the positioning system as it reveals the variation in its performance over many trials. Here, the cumulative probability function of the distance error between the estimated and true location is used to illustrate the precision of the systems under consideration.

Moreover, localization system designers often need to address multiple, possibly competing, requirements by balancing tradeoffs in terms of accuracy, precision, and system complexity. Here, system complexity can be attributed to *hardware complexity* and *software complexity*. Given that we do not have access to the source code of the solutions under comparison, we only examined their hardware requirements.

For a typical indoor localization system, hardware components usually consist of mobile nodes, external base stations, and central computing infrastructures. More specifically, mobile nodes are often rested on target devices and could be one of the following: radio transceivers (e.g. WiFi, Bluetooth, ZigBee, or UWB), RFID tags, or light sensors with necessary microprocessors and other circuit elements. Interestingly, modern smartphones have packed a variety of sensors, wireless communication, and desirable computing capability into a small form factor, which encourages many researchers to use them as mobile nodes in various applications. Although two candidates [14][25] in Table II adopted this method for its convenience and the devices they chose may seem too demanding for IoT applications, we consider the overall solutions inspiring and believe that they could be remodeled to fit other IoT scenarios. Therefore we included them in the comparison list, with an emphasis on the contributing hardware components instead of the smartphone as a whole.

Meanwhile, WiFi access points, RFID readers, and LEDs serving as base stations can be easily found in the literature. Both cloud servers and dedicated desktop computers have been used as central computing infrastructures for location estimation. Given that base stations and backend servers can be connected to the grid without concern for power consumption, we only point them out in the last column for reference.

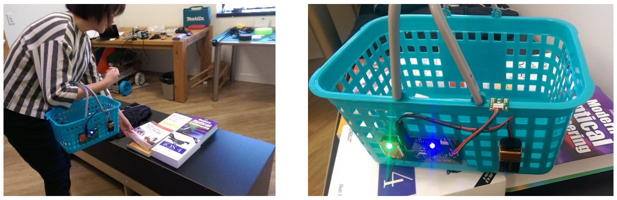
Closely related to system complexity, building cost represents another dimension of localization system evaluation. However, the cost of a particular system may depend on many factors, including manpower, time, space, and energy. Considering that most existing studies did not reveal the details about their deployment overhead and development cost, we think it is not appropriate for us to make any statement on this matter.

Furthermore, in this work we focus our attention on the case of low-power IoT devices. Indoor localization technologies using computing vision, laser scanners, and pedestrian dead reckoning (PDR) are not considered, given the diversity of the appearance of IoT devices, the size and power consumption of laser scanners, and the requirement of working pedestrians, respectively.

Finally, it can be seen from Table II that this evaluation study allows us to closely compare our proposed system with other strategies for indoor localization in the context of IoT applications. Even though these candidates do not cover every single research and industry effort in this field, they are representative of the most promising indoor localization technologies that can be integrated into either existing or future IoT devices. Based on this analysis, we believe we can safely say that Foglight holds significant promise for location-based IoT applications with appealing accuracy, robustness, and simplicity. As shown in the third and forth column, Foglight achieves the highest accuracy and precision compared to all other candidates. Further, Foglight is simple in design with the need of only off-the-shelf components: lightsensors, entry-level microcontrollers, and DLP projectors installed in the environment.

VI. EXAMPLE APPLICATION

We now demonstrate two example applications of Foglight: *customer tracking in grocery stores* and *visitor tracking in museums*. These are strong candidates for large-scale, high-accuracy and real-time indoor localization applications



(a) (b)

Fig. 11. (a) A shopping scenario setup. (b) A shopping basket augmented with Foglight.

considering that the advertising industry is beginning to expect localization accuracy at the granularity of an aisle or even a set of products in a grocery store [49], and museums are expecting visitor locations at the granularity of paintings [50] so that tourists can automatically receive information about the artifacts that they walk by. Part of our exploration of these scenarios involved producing and testing a proof-of-concept application for each use context, the outcome of which we present below.

A. Shopping Behavior Tracking

For most people, grocery shopping is a routine activity repeated frequently. Researchers have shown much interest in understanding people's in-store shopping behavior through location tracking. The specific aspects they have examined include *the number of aisles shopped*, *time spent in the store*, *stay duration in front of different items*, and more.

Our sensor could be easily incorporated into shopping carts or baskets, turning them into tracking devices that can provide real-time customer location inside the store. Imagine you’re in a store, and you’re wandering around the shoe section trying on different pairs of boots. The system detects this and sends you targeted content on how to find the best fit for a boot in your size, a video interview with the shoe designer of the pair you’re looking at, or even a discount coupon that would apply if you make the purchase.

We simulated this scenario by resting some books and clothes on a table inside the projection area to mimic the shopping scenario (Fig. 11a). A shopping basket was also augmented with the sensor unit to provide real-time location (Fig. 11b). Further, it is not unusual for a localization system to anticipate the moving direction of a target device/user. By embedding two light sensors on a single sensor unit, Foglight could determine a customer’s moving direction easily.

B. Museum Behavior Tracking

Museums are another beneficiary of location-enabled IoT technology [51]. Our sensor could be combined with the user’s mobile device or incorporated into existing devices in the museum, for example audio guides, to provide real-time, fine-grained indoor location of visitors. Therefore, instead of searching through an audio tour for a specific section, a visitor can instantly watch a video highlighting the artist’s life on his/her mobile device and learn more about a painting once he/she is close to the artifact. Consider another example where the museum manager wants to increase the time people spend at the museum. The museum can offer a scavenger hunt [52], with clues that pop up on the user’s mobile screen at every corner of

Fig. 12. A student is using Foglight to receive media files about artifacts.

the building. Alternatively, Foglight could send visitors notifications to highlight events that took place when the artifact was created, given that one of the factors that have a strong influence on art and science is the time period in which it was created. With these applications, visitors will be entertained and educated. Additionally, their visiting experience would be significantly enhanced thanks to these location-based services.

Meanwhile, Foglight can also be used for gathering data to gain insights on visitor’s behavior, which can then be used to improve exhibit locations and museum layouts, thus enhancing the overall visitor experience. Specifically, Foglight can be used to measure *dwell times*, meaning how much time visitors spend at different locations of the museum, or which exhibits are most popular. This helps the exhibit organizer understand if an exhibit is popular by itself or if it is due to its placement at a specific location. A visitor’s entire tour can be tracked, providing invaluable data about how long they stayed, which sections they visited, and countless other behavior metrics regarding their visit, such as the time spent at each section, interests, and artifact purchase history.

We built a simple, proof-of-concept location-based multimedia player that lets users trigger context information on their mobile phones. Users can receive multimedia files related to the artifact they are looking at, add comments to it, and share their experience with other visitors on their mobile phones. This is made possible by having the projection simultaneously serve a dual purpose, both for illumination and for transmitting location information to the sensor unit on the visitor’s mobile device. As shown in Fig. 12, a student is using Foglight to receive a video file about a painting in our simulated museum scenario. The dot at top left indicates the location of the device inside the projection area and the image at bottom left shows what the student sees on his mobile phone.

VII. Contribution & Future Work

The salient distinguishing feature of Foglight is that all pixels inside the projection area have been encoded with location information and the only step needed to restore the corresponding coordinates for a particular sensor unit is to collect a sequence of sensor readings and convert the codeword to its original coordinates. This important property sets it apart from all existing indoor localization system. Further, our technology is sufficiently low-power and inexpensive to enable integration into existing location-based IoT services and the Fog Computing paradigm. Location data communication in Foglight takes place in a unidirectional fashion from the DLP projector to the sensor unit. This simplicity allows us to maintain a minimum system design, not requiring a central infrastructure or a network server for heavy computation. Finally, with Foglight, indoor localization and tracking occur in real time, as illustrated in the system evaluation section. This property can be particularly critical within the Fog Computing context, where low latency is highly preferred.

At present, Foglight also has several drawbacks. First, it can only provide 2D location information. Further, we only tested our current implementation with one projector; learning how to stitch multiple DLP projectors together to provide indoor locations at a larger scale needs to be explored. A potential approach is to assign a unique identification to each projector and add a few naming frames at the beginning of the projected patterns so that a target light sensor can easily differentiate the source of received light signals. Modulating the light from the projectors with different carrier signals would also be necessary to avoid interference.

In addition, considering gray codes have a $O(\log_2 n)$ relationship between the number of required patterns and the total number of pixels of the projecting devices, projectors with more pixels and higher projection rates can be explored to improve localization accuracy and system refresh rate. Moreover, although our experimental results are promising, robustness needs to be improved for real world cases. For example, we are working on the next version of Foglight, in which the location information is transmitted through a modulated visible light channel with a 480 kHz carrier. This could significantly improve the signal-to-noise ratio, and thereby the overall performance of Foglight, which would allow us to track target devices under various challenging conditions.

Finally, the reason that Foglight is suitable for low-power IoT devices is that the sensor unit itself only needs to decode time-multiplexing light signals to restore its own location using simple light sensors. Through our extensive experiments, the designed hardware system consumes ~25 mA current while decoding the received light signals at the frequency of 84 Hz. This does not include the power consumption of the WiFi module for data transmission, which in practice consumes about 85 mA for transmission. Other low-power communication technologies, such as Bluetooth Low Energy, can be utilized to reduce this part to around 16 mA [53]. However, the DLP projector itself still consumes a certain amount of power (around 15 Watts) in our current prototype. Although they can be connected to the grid without the worry of running out of power, more effort is needed to evaluate the likelihood of reducing energy consumption.

VIII. Conclusion

In this paper, we have described how off-the-shelf DLP projectors and light sensors can be used to locate IoT devices in an indoor environment with high accuracy, low latency, and low computation overhead. We integrated this technique into different real life objects and built two demo applications to highlight some basic uses of location-aware IoT services. The evaluation of our sensing technique revealed that Foglight holds significant promise for future research.

References

[1] S. Sen, J. Lee, K.H. Kim, and P. Congdon, "Avoiding multipath to revive inbuilding WiFi localization," in *Proc. ACM MobiSys*, 2013, pp. 249-262.
[2] L. Wirola, T. Laine, and J. Syrjrinne, "Mass-market requirements for indoor positioning and indoor navigation," in *Proc. IEEE IPIN*, 2010, pp. 1–7.
[3] C. Röhrig and M. Müller, "Indoor location tracking in non-line-of-sight environments using a IEEE 802.15. 4a wireless network," in *Proc. IEEE/RSJ IROS*, 2009, pp. 552-557.
[4] D. Lymberopoulos, J. Liu, X. Yang, R. R. Choudhury, V. Handziski, and S. Sen, "A realistic evaluation and comparison of indoor location technologies: experiences and lessons learned," in *Proc. ACM/IEEE IPSN*, 2015, pp. 178-189.
[5] Z. Zhang, X. Zhou, W. Zhang, Y. Zhang, G. Wang, B. Y. Zhao, and H. Zheng, "I am the antenna: accurate outdoor AP location using smartphones," in *ACM MobiCom*, 2011, pp. 109-120.
[6] B. Alavi and K. Pahlavan, K., "Modeling of the TOA-based distance measurement error using UWB indoor radio measurements," *IEEE Communications Letters, 2006, 10(4)*, pp.275-277.
[7] K. Chintalapudi, A. Padmanabha Iyer, and V.N. Padmanabhan, "Indoor localization without the pain," in *Proc. ACM MobiCom*, 2010, pp. 173-184.
[8] M.S. Bargh and R. de Groote, "Indoor localization based on response rate of bluetooth inquiries," in *Proc. ACM MELT*, 2008, pp. 49-54.
[9] S. He and S. Chan, "Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons," *IEEE Communications Surveys & Tutorials. 18(1)*, pp. 466-490.
[10] M. Roshanaei and M. Maleki, "Dynamic-KNN: A novel locating method in WLAN based on Angle of Arrival," In *Proc. IEEE ISIEA*, 2009, pp. 722-726.
[11] M. Shimosaka, O. Saisho, T. Sunakawa, H. Koyasu, K. Maeda, and R. Kawajiri, "ZigBee based wireless indoor localization with sensor placement optimization towards practical home sensing," *Advanced Robotics, 2016, 30(5)*, pp. 315-325.
[12] T. Alhmiedat, G. Samara, and A. O. A. Salem, "An indoor fingerprinting localization approach for ZigBee wireless sensor networks," *arXiv preprint arXiv:1308.1809, 2013.*
[13] D. Gundegard, A. Akram, S. Fowler, and H. Ahmad, "Cellular positioning using fingerprinting based on observed time differences," in *Proc. IEEE SaCoNeT*, 2013, pp. 1-5.
[14] E. Dahlgren and H. Mahmood, "Evaluation of indoor positioning based on Bluetooth Smart technology," M.S. thesis, Dept. Comp. Sci. and Eng., Chalmers University of Technology, Sweden, 2014.
[15] A. Popleteev, "AmbiLoc: A year-long dataset of FM, TV and GSM fingerprints for ambient indoor localization," in *Proc. IEEE IPIN*, 2017. [Online]. Available: http://orbilu.uni.lu/bitstream/10993/32587/1/ipin2017-dataset.pdf
[16] V. Moghtadaiee and A. G. Dempster, "Indoor location fingerprinting using FM radio signals," *IEEE Transactions on Broadcasting. 60(2)*, pp. 336-346.
[17] D. A. Tesch, E. L. Berz, and F. P. Hessel, "RFID indoor localization based on Doppler effect," in *Proc. IEEE ISQED*, 2015, pp. 556-560.
[18] S. Ma and Y. Shi, "A scalable passive RFID-based multi-user indoor location system," in *Proc. IEEE WiCOM*, 2011, pp. 1-4.
[19] K. Yu, "3-D localization error analysis in wireless networks," *IEEE Transactions on Wireless Communications. 6(10)*, pp. 3473-3481.
[20] A. Makki, A. Siddig, M. Saad, J. R. Cavallaro, and C. J. Bleakley, "Indoor localization using 802.11 time differences of arrival," *IEEE Transactions on Instrumentation and Measurement*. 65(3), pp. 614-623.
[21] T. Van Haute, B. Verbeke, E. De Poorter, and I. Moerman, "Optimizing Time-of-Arrival Localization Solutions for Challenging Industrial Environments," *IEEE Transactions on Industrial Informatics*. 13(3), pp. 1430-1439.
[22] N. A. M. Razali, M. H. Habaebi, N. Zulkurnain, M. Islam, and A. Zyoud, "The Distribution of Path Loss Exponent in 3D Indoor Environment," *International Journal of Applied Engineering Research*. 12(18), pp. 7154-7161.
[23] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *Proc. IEEE INFORCOM*, 2000, pp. 775-784.
[24] M. Youssef and A. Agrawala, "The Horus WLAN location determination system," in *Proc. ACM MobiSys*, 2005, pp. 205-218.
[25] C. Beder and M. Klepal, "Fingerprinting based localisation revisited—a rigorous approach for comparing RSSI measurements coping with missed

access points and differing antenna attenuations," in *Proc. IPIN*, 2012, pp. 1-7.

[26] D. Lymberopoulos and J. Liu, "The Microsoft Indoor Localization Competition: Experiences and Lessons Learned," *IEEE Signal Processing Magazine, 34(5)*, pp.125-140. Sep. 2017.

[27] J.S. Lee, Y. W. Su, and C. C. Shen, "A comparative study of wireless protocols: Bluetooth, UWB, ZigBee, and Wi-Fi," in *Proc. IEEE IECON*, 2007, pp. 46-51.

[28] M. Z. Win and R. A. Scholtz, "On the robustness of ultra-wide bandwidth signals in dense multipath environments," *IEEE Communications letters, 2(2)*, pp. 51-53.

[29] Quantitec Intranav. Available: https://intranav.com

[30] A. F. Molisch, J. R. Foerster, and M. Pendergrass, "Channel models for ultrawideband personal area networks," *IEEE wireless communications, 10(6)*, pp. 14-21.

[31] J. Mao, M. Sarmiento, Q. Zhou, J. Chen, P. Wang, Z. Zou, F. Jonsson, and L.R. Zheng, "A 90nm cmos uhf/uwb asymmetric transceiver for rfid readers," in *Proc. IEEE ESSCIRC,* 2011, pp. 179-182.

[32] Z. Yang, Z.Wang, J. Zhang, C. Huang, and Q. Zhang, "Wearables can afford: Light-weight indoor positioning with visible light," in *Proc. ACM MobiSys*, 2015, pp. 317-330.

[33] Y.S. Kuo, P. Pannuto, K.J. Hsiao, and P. Dutta, "Luxapose: Indoor positioning with mobile phones and visible light," in *Proc. ACM MobiCom*, 2014, pp. 447-458.

[34] B. Xie, G. Tan, and T. He, "SpinLight: A high accuracy and robust light positioning system for indoor applications," in *Proc. ACM SenSys*, 2015, pp. 211-223.

[35] P. Hu, L. Li, C. Peng, G. Shen, and F. Zhao, "Pharos: enable physical analytics through visible light based indoor localization," in *Proc. ACM HotNet*, 2013, pp. 1-7.

[36] L. Li, P. Hu, C. Peng, G. Shen, and F. Zhao, "Epsilon: A Visible Light Based Positioning System," in *Proc. USENIX NSDI*, 2014, pp. 331-343.

[37] C. Zhang, J. Tabor, J. Zhang, and X. Zhang, "Extending Mobile Interaction Through Near-Field Visible Light Sensing," in *Proc. ACM MobiCom*, 2015, pp. 345-357.

[38] H. Zou, H. Jiang, X. Lu, and L. Xie, "An online sequential extreme learning machine approach to WiFi based indoor positioning," in *Proc. IEEE WF-IoT*, 2014, pp. 111-116.

[39] T.Y. Wu, G.H. Liaw, S.W. Huang, W.T. Lee, and C.C. Wu, "A GA-based mobile RFID localization scheme for internet of things," *Personal and Ubiquitous Computing, 2012, 16(3),* pp.245-258.

[40] S. Alletto, R. Cucchiara, G. Del Fiore, L. Mainetti, V. Mighali, L. Patrono, and G. Serra, "An indoor location-aware system for an iot-based smart museum," in *IEEE Internet of Things Journal*, *2016, 3(2),* pp.244-253.

[41] S. Ma, Q. Liu, and P. Sheu, "On hearing your position through light for mobile robot indoor navigation," in *Proc. IEEE ICMEW*, 2016, pp. 1-6.

[42] S. Inokuchi, K.O.S.U.K.I. Sato, and F. Matsuda, "Range imaging system for 3-D object recognition," in *Proc. ICPR*, 1984, pp. 806-808.

[43] Manchester code. Wikipedia. [Online]. Available: https://en.wikipedia.org/wiki/Manchester_code

[44] S. M. Berman, D. S. Greehouse, I. L. Bailey, R. D. Clear, and T. W. Raasch. Human electroretinogram responses to video displays, fluorescent lighting, and other high frequency sources. *Optometry & Vision Science, 68(8)*, pp. 645-662.

[45] *findHomography*. OpenCV. [Online]. Available: http://docs.opencv.org/2.4/modules/calib3d/doc/camera_calibration_and_3d_reconstruction.html?highlight=findhomography

[46] *1 Key Touch Pad Detector IC*. [Online]. Available: https://www.elecrow.com/download/TTP223_SPEC.pdf

[47] M. Wright and A. Freed, "Open sound control: A new protocol for communicating with sound synthesizers," in *Proc. ICMC*, 1997, pp. 10.

[48] F. Hammer, M. Pichler, H. Fenzl, A. Gebhard, and C. Hesch, "An acoustic position estimation prototype system for underground mining safety," *Applied Acoustics*, *92*, pp.61-74.

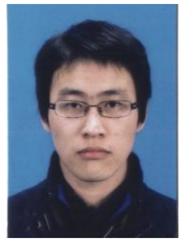
[49] Placecast. [Online]. Available: http://placecast.net/index.html

[50] E. Bruns, B. Brombach, T. Zeidler, and O. Bimber, "Enabling mobile phones to support large-scale museum guidance," in *Proc. IEEE Multimedia, 14(2)*, pp. 16-25.

[51] S. Ma, Q. Liu, and H. Tang, "An Overview of Location Semantics Technologies and Applications," *International Journal of Semantic Computing, 2015, 9(03),* pp. 373-393.

[52] Scavenger hunt. Wikipedia. [Online]. Available: https://en.wikipedia.org/wiki/Scavenger_hunt

[53] BlueCreation BC118. http://www.digikey.com/product-detail/en/bluecreation/BC118/1495-1003-1-ND/4860037



Shang Ma (M'12) received the B. S. degree in Optical Communication from Zhejiang University, China, in 2009 and M.S. degree in Computer Science from Tsinghua University, China, in 2012. He is working toward the Ph.D. degree in Computer Engineering at University of California, Irvine, CA, USA.

He is also an Adjunct Researcher at FX Palo Alto Laboratory. His research interests include intelligent embedded system, indoor localization, IoT, and ubiquitous computing.

Qiong Liu received the B.E. degree in scientific instrument from Zhejiang University in 1989, the M.E. degree in precision instrument from Tsinghua University in 1992, and the Ph.D. degree in computer science from University of Illinois at Urbana-Champaign (UIUC) in 2001.

He is currently a principal research scientist at Fuji-Xerox Palo Alto Laboratory (FXPAL) in Palo Alto, California. His research interests include image/video/audio processing, multimedia, robotics, computer vision, speech recognition, machine learning, human-computer interaction, augmented reality, PaperUI, indoor localization, object/document recognition, immersive conferencing, and IR-camera based vital sign detection. He has published over 70 articles in international conferences and journals and has over 100 pending and issued patents.

Phillip C.-Y Sheu (F'03) received the B.S. degree from National Taiwan University and the M.S. and Ph.D. degrees in electrical engineering and computer science from the University of California at Berkeley.

He is currently a Professor of Electrical Engineering and Computer Science, Computer Science, and Biomedical Engineering with the University of California, Irvine.

Prof. Sheu is the founder of the Institute for Semantic Computing and Robotic Computing, founding chair of the IEEE Computer Society Technical Committee on Semantic Computing, founder of the IEEE International Conference on Semantic Computing, founding editor-in-chief of the International Journal of Semantic Computing, founding editor-in-chief of the Encyclopedia with Semantic Computing, a co-founder of the IEEE International Conference of Multimedia Big Data, and a co-founder of the IEEE International Conference on Robotic Computing.