NaviLight: Indoor Localization and Navigation Under Arbitrary Lights

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***Abstract*—Thanks to the highly-dense lighting infrastructure in public areas, visible light emerges as a promising means to indoor localization and navigation. State-of-the-art techniques generally require customized hardware (sensing boards), and mainly work with one single light source (*e.g.*, customized LEDs). This greatly limits their application scope. In this paper, we propose NaviLight, a generic indoor localization and navigation framework based on existing lighting infrastructure with *any unmodified* light sources (*e.g.*, LED, fluorescent, and incandescent lights). NaviLight simply adopts commercial *off-the-shelf* mobile phones as receivers, and light intensity values as location signatures. Unlike existing WiFi systems, a single light intensity value is not discriminative enough over space though the light intensity field does vary, which makes our design more challenging. We thus propose a *LightPrint* as a location signature using a *vector* of multiple light intensity values obtained during user's walks. Such LightPrints are created by leveraging any user movement (of varying distance and direction) in order to minimize user efforts. A set of techniques are proposed to achieve quick LightPrint matching, which includes a coarse-grained classification and a fine-grained matching over dynamic time warping. We have implemented NaviLight to provide real-time service on Android phones in three typical indoor environments, covering a total area size over $1000m^2$. Our experiments show that NaviLight can achieve sub-meter localization accuracy to meet practical engineering requirements.**

I. Introduction

Lighting infrastructure has already been in place to provide ubiquitous service, especially in public indoor environments such as shopping malls, offices, and parking lots, *etc.*. Due to its ubiquity and density, visible light becomes a promising medium for indoor localization and navigation [1]–[7]. Nevertheless, existing systems have a fundamental limitation: they are not entirely compatible with the current lighting infrastructure. In contrast, they mainly adopt a single type of programmable LEDs (light-emitting diode) to deliver essential information (*e.g.*, broadcast LED IDs and/or landmark positions), as well as customized hardwares for light measurements (*e.g.*, intensity). As pointed out in [8], [9], other light sources such as fluorescent bulbs and high-intensity discharge lamp contribute to more than 80–90% of public indoor environments in the US, and thus LED is indeed far from dominating the market. This makes LED-based systems hard to be widely deployed in practice.

As such, in this work we consider arbitrary light sources in general indoor environments to propose a visible light localization system NaviLight. It is motivated by the concept of light fingerprints. As a matter of fact, light intensity attenuates at different locations when the light propagates in the air. This makes light intensity a possible metric to generate fingerprints for localization. NaviLight is easy-to-deploy, yet low-cost with high-accuracy. It is adaptive to various indoor environments, and thus fully compatible with existing lighting infrastructure for a wide deployment scope.

Since NaviLight relies on inertial light sensors on commercial off-the-shelf (COTS) mobile phones to gauge light intensity, no special hardware is required and all communication between lighting infrastructure and phones (including passive reception of bulb beaconing) are removed. This makes it practical with low-cost. To the best of our knowledge, NaviLight is the first practical system for generic localization and navigation which is ready to use under arbitrary unmodified light infrastructures.

Though the idea of NaviLight is inspired by indoor positioning systems using WiFi radar (which takes signaling strength as fingerprints) [10], it faces three distinct issues: (1) Light intensity is much more coarse-grained and ambiguous over space as compared with the electronic counterpart; (2) Unlike WiFi-based systems, there is no any communication between sources/lamps and targets/users, and thus the former cannot serve as landmarks to the latter; (3) Due to the above two issues (under rich ambiguity but without communication), the size of the design problem becomes large and thus quick matching between user movements and pre-collected *light intensity field (LIF)* fingerprints is also a hard problem. These issues make real-time high-accuracy localization a big challenge.

To address the above issue (1), we carry out an in-depth study on the properties of light intensity by experiments. We find that a single intensity value at a fixed point is generally not sufficient to serve as a good location signature. Instead, a *vector* of multiple light intensity values along the user walk trace (defined as a *LightPrint*) is much more suitable (See Sec. II), *i.e.*, LightPrint is discriminative in space and stable over time. Therefore, NaviLight collects LightPrint during a user's walks, and match it with the pre-built LIF map to estimate the user's location.

The above issue (2) indicates that, in NaviLight a user can only depend on the observed LightPrint for localization, rather than geographic landmarks obtained by signalings as in the WiFi case. To this end, the problem of identifying the

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LightPrint from the LIF map is relatively large in size due to vector dimension of the LightPrint and free roaming of the user, especially when the size of the plane area is large (*e.g.*, one of our experiments is performed in an office building over $4000m^2$). On the other hand, our localization algorithm must be scalable enough to handle the large-size problem and provide real-time service. To tackle this dilemma, we adopt a divide-and-conquer technique. It divides the whole floor plane into multiple subareas. Then, KNN (K-Nearest Neighbor classification) is invoked to achieve a coarse-grained localization (see Section IV-A) among all subareas before another fine-grained localization is carried out for each subarea.

The above issue (3) concerns about complexity and accuracy of the localization algorithm. A LightPrint corresponds to a curve in a physical space, since it is collected during walks which might be at any directions or even with turns. Clearly, matching a curve (corresponding to the LightPrint) against a surface (corresponding to the LIF map) is highly intensive in computation [10], especially when the LightPrint size varies with the user's different walking speed (even the walk trace keeps the same). Furthermore, regularities of LIF map increase ambiguity in LightPrint identification. As a result, the matching algorithm must be sufficiently efficient and elastic. Accordingly, we first partition a LighPrint into multiple linear short segments with one direction for each, where walk direction is obtained leveraging IMU (Inertial Measurement Unit) of mobile phones. Then we match the corresponding directed and segmented LightPrint against light intensity sequences in the LIF map, leveraging subsequence DTW (Dynamic Time Warping) algorithm (Sec. III-C). In this way, curve-surface matching problem turns into a time-sequence matching one, which can significantly reduce computational complexity. Moreover, DTW can well match two time-sequences with different speeds. To deal with the ambiguity caused by LIF regularities, we propose a clustering approach based on DTW distances to find the best match (Sec. III-D).

We implement the sensing function as an Android application and deploy the NaviLight localization and navigation service at a server. We verify NaviLight in three respective environments, including an office building, a shopping mall and an underground parking lot, with a total area size of over 1000m^2. We build LIF maps for all the scenarios, and collect LightPrints by walking randomly in each scenario as test datasets. Experiment results confirm that using LightPrints yields high localization accuracy. In particular, 85% of errors for indoor localization are within 0.5m (office), 0.35m (mall) and 3.9m (an underground parking lot, 59% of errors within 1.0m); for navigation, 85% of errors are within 1.6m, 2.2m and 4.3m respectively.

In summary, we make three key contributions:

- Unlike all existing works which rely on communication with lamps for localization, we propose a novel concept of LightPrint without the need of any signaling. LightPrint is featured by using a vector of light intensity values to increase localization accuracy.

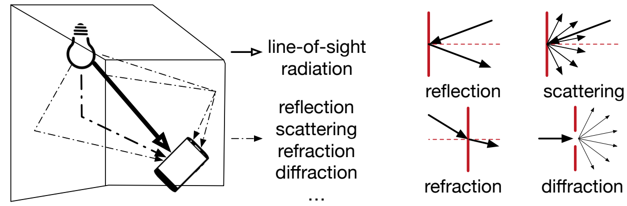


Fig. 1: Light propagation in reality: radiation, reflection, refraction, diffraction, and scattering.

- We propose a suite of efficient and scalable algorithms for localization and navigation in large-size indoor environments, which are self-adaptive to different environments and user movement patterns.
- We implement NaviLight and deploy real-time localization service in three typical indoor environments to demonstrate its practical effectiveness and sub-meter accuracy.

II. Feasibility Study of NaviLight

In this section, we investigate whether light intensity is stable and discriminative enough to act as a suitable location signature. For this purpose, we carry out extensive experiments in real world to characterize the light intensity field (LIF).

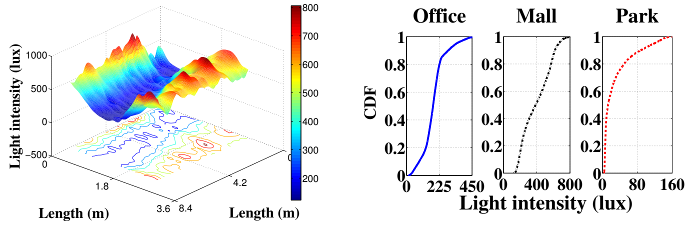
A. Lighting Primer

Lamp bulbs turn electric current into light. Based on various lighting mechanisms, there are several popular types of bulbs in use: light-emitting diode (LED), linear fluorescent lamp (LFL), compact fluorescent lamp (CFL), incandescent light bulb (ILB) and high-intensity discharge lamps (HID), to name a few [8], [9]. Generally, light attenuates as it propagates in the air, leading to various radiant intensities at different positions (Figure 1). In the ideal case where the light experiences only line-of-sight radiation, the luminous intensity follows Lambert's emission law [11].

It turns out that, light intensity produced by even a single source may not be uniformly distributed due to the impact of the surroundings. This is because of reflection, scattering, refraction and diffraction (see Fig. 1), where different surfaces have different light reflection factors [12]. For example, a white smooth wall and a colorful curtain reflect, scatter or absorb the light in different ways. Besides, bulbs are often covered with (possibly) irregular decorative panels and lamp shades made from different materials, and light may be displaced as well. In practice, lighting infrastructure consists of various types of light sources, leading to an even more complex distribution of LIF. As a result, the LIF in real environment is not uniformly distributed, which makes it sufficiently discriminative (validated in the following experiments).

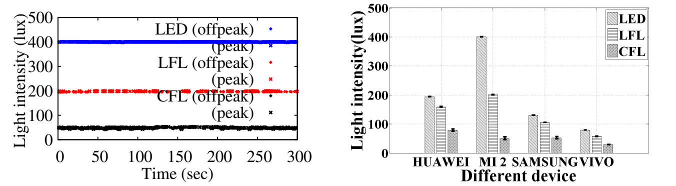
B. Spatial Discrimination

Experimental setting Our experiment setting complies with typical indoor environments: one office building, a shopping mall, and an underground parking lot (See Fig. 9). Commodity



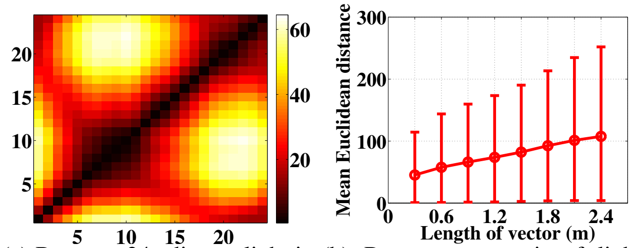
(a) Light intensity Field in a mall (b) CDF of Light intensities

Fig. 2: Light intensity distribution.



(a) MI 2 under different lights (b) Stability over various receivers

Fig. 4: Temporal stability of light intensity.



(a) Between 24 adjacent light intensity vectors. (b) Between any pair of light intensity vectors with different length

Fig. 3: Euclidian distance.

smartphones equipped with light sensors are used to measure luminous intensities at various spots, and four Android phone models are tested (Xiaomi MI2, Samsung Note3, Blu Vivo 5 and Huawei Honor 7i). The absolute intensity value is phone-dependent but the patterns are similar to each other. Therefore, we present the results using MI2 unless otherwise specified.

Location dependent fading effect Spatial discrimination is first examined. Fig. 2(a) shows the LIF measured over a small area in a shopping mall. Fig. 2(b) gives the cumulative distribution function (CDF) of the observed values. We can observe that 1) the light intensity varies over space. It is strongest right under the lamp and gradually attenuates in the periphery. Its distribution varies as well; 2) the light intensity distribution is less regular than anticipated (an ideal circle); and 3) diversity is more significant in the mall and office (with irregular bulb deployment and floor plan) than in the parking lot (with regular bulb deployment over a large open space). This implies that light intensity may be used as a suitable location signature. Nevertheless, a single light intensity value can only offer very limited discrimination, since many other spots (*e.g.*, those on the contours) may have the same light intensity value.

Spatial discrimination of light intensity vectors To enhance discrimination of light intensity, we increase the spatial coverage of measurements to get a *vector* of light intensity values, or defined as a *LightPrint*. Each of its entry denotes a light intensity value of a spot on the walking trace. Whenever we mention “length” of a LightPrint hereafter, we mean a walking distance on the trace that is used to produce the vector based LightPrint. Note that “length” is different from “size” where the latter refers to the number of entries in the vector.

We further study the spatial discrimination of the LightPrint. Without loss of generality, 24 LightPrints are randomly chosen from each LIF. Each LightPrint is assigned an index number, and two closer index numbers mean that the corresponding LightPrints also have a closer spatial distance. Intuitively, we use Euclidian distance to denote discrimination in Fig. 3(a). A point in Fig. 3(a) matches a pair of LightPrints, where the horizontal axis indexes one LightPrint and the vertical axis indexes another one. The discrimination is indicated by different colors, where a deeper color denotes a smaller discrimination (Euclidian distance). It is obvious that, the colors in Fig. 3(a) are symmetric to the main diagonal (from down left to up right).

Generally, a pair of LightPrints with a closer spatial distance leads to a smaller discrimination. In particular, the discrimination is zero if the two LightPrints are exactly the same. As a result, Euclidian distance may provide a relatively good discrimination among LightPrints, but this is not always true. In fact, some LightPrint pairs with a remote spatial distance may also have a small discrimination. For example, vector 1 and 24 have a short Euclidian distance.

We now examine how LightPrint length can affect discrimination. Fig. 3(b) is obtained by choosing LightPrints with length varying from 0.3m to 2.4m with a step size of 0.3m, and calculating Euclidian distances for LightPrints with the same length. We can see that the mean Euclidian distance increases with the LightPrint length, and thus becomes more discriminative.

In short, we conclude that LightPrint is pretty discriminative, which is related to the LightPrint length. However, Euclidian distance is not sufficient to depict LightPrint discrimination. Therefore we need to find other metrics for discrimination.

C. Other Factors

Temporal stability As shown in Fig. 4(a), light intensity varies only within 5 lux for every lamp type. For each light source, we spend one month to measure light intensity at the same place for peak/off hours on different dates, with fixed phone locations. We find that light intensity at the same place is stable over time.

Device diversity and stability By using different phones as receivers, it is observed that the results (as shown in Fig. 4(b)) are very stable for each phone, but diverse for different phones due to sensor sensitivity. However, the pattern

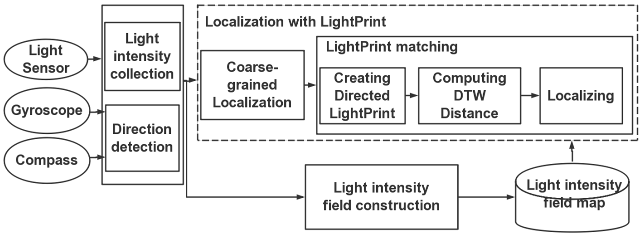


Fig. 5: Architecture of NaviLight.

remains invariant for different phones (see Sec. III-D). This makes it possible to develop the same LightPrint for a wide variety of receiver types.

III. NaviLight Design

NaviLight enables a user to get convenient real-time localization and navigation service in buildings, typically in large shopping malls or underground parking lots. A user just needs to walk straight or along a preplanned path for a few steps, carrying a mobile phone in hand with front upside to receive lights and produce LightPrints. User location is then estimated by matching LightPrints against pre-built LIF maps. Notably, the matching algorithm is run at a server (rather than on the phone) after sensor data is sent to the server. This avoids energy/resource-consuming computations on the phone.

As shown in Fig. 5, NaviLight is composed of two key modules: coarse-grained localization and LightPrint matching.

Coarse-grained localization via KNN. In order to make NaviLight scalable, a LightPrint collected during a walk is first classified into one of subareas of the building's floor plan via coarse-grained localization algorithm based on KNN.

LightPrint matching based on DTW distance. Before matching, a LightPrint is divided into one or several light intensity vectors with specific walking directions, *i.e.*, directed LightPrints. Then the directed LightPint is matched with LIF map leveraging subsequence DTW. Finally, the best match is found out based on DTW distances by a clustering technique.

A. Coarse-Grained Localization via KNN

To make localization algorithm scalable, we adopt the idea of divide and conquer. We first localize the LightPrint into one of subareas of the floor. Then a fine-grained LightPrint matching only needs to take each small subarea into account to find the accurate location. In this way, performance of NaviLight is independent of the large floor size and the proposed framework is scalable.

In particular, the LIF map of a building floor can be divided into multiple smaller subareas according to their physical forms and sizes, as detailed in Sec. IV. We localize the LightPrint into one of the subareas via KNN algorithm. This is inspired by observations that LIF maps vary among different sub-areas, due to the following fact:

(1) The type and deployment densities of luminaires are usually different from subarea to subarea.

(2) The surroundings (*e.g.*, decorations and walls) are often different too. This affects light intensity since different surface has different light reflection factor [12].

However, it is difficult to determine the distribution of a LightPrint, even though we know the LIF map in advance. In this case, KNN can serve as a fundamental and simple classification method [13]. Since KNN is a well-known classifier, we omit the details here.

Unfortunately, an exception may occur where the coarse-grained (subarea level) localization may be erroneous, even though the classification accuracy can reach 100% in the training stage. In this case, subsequent LightPrint matching for a subarea is in vain. Our LightPrint matching algorithm detailed in Sec. III-D can avoid this exception by detecting possible classification errors.

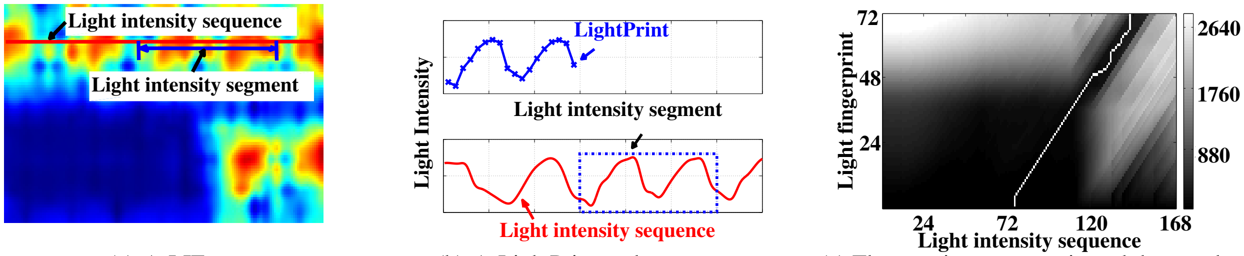
B. Creating Directed LightPrints

LightPrints may be curves in a physical space, since they are collected during walks with possible direction changes. However, light intensities collected are pure time sequences without direction attributes. So far, our definition on LightPrint has not incorporated direction attributes. More seriously, even if directions had been incorporated, matching a curve (LightPrint) against a surface (LIF map) involves nontrivial computational complexity [10]. In contrast, matching a linear LightPrint could be much easier. For those two reasons, we need to define *directed* LightPrints, which are obtained by breaking a LightPrint vector into multiple smaller-size vectors with one direction for each (denoting the instant walking direction of the user at a corresponding point on the walk trace). By using directed LightPrints, the curve-surface matching problem can then be turned into a linear time-sequence matching problem, leading to a much lower computational cost.

It is challenging to estimate instant walk directions by IMU sensors (gyroscope and compass) built in mobile phones, due to complicated walk patterns and indoor magnetic interference [14]–[16]. Since the phone is needed to face up to collect light intensity, it is reasonable to assume that the phone attitude is constant, and the phone heading is identical to the walk direction (we will relax this assumption in our future work). Then, the walk direction can be estimated by combing compass and gyroscope sensor readings using a complementary filter as in [6]. We use gyroscope sensor readings to detect direction changes, by which a curved LightPrint can be partitioned.

C. Computing DTW Distances

Before we match directed LightPrints against LIFs, we have to notice that sizes of LightPrints vary even though they are collected from the same walk trace. This is caused by different walk speeds. LIFs are constructed in advance, whereas LightPrints are collected when people need localization services. Different people may walk at different speeds and it is impossible to be the same as that when LIFs are built. Fortunately, dynamic time warping is such a technique to align and measure the similarity between two time sequences with



(a) A LIF (b) A LightPrint and a sequence (c) The warping cost matrix and the matched segment

Fig. 6: LightPrint matching via Subsequence DTW.

different speeds. As a similarity measure, DTW distance is defined as follows, which can be computed in O(NM) using dynamic programming [18].

DTW distance Let $X := (x_1, x_2, \ldots, x_N)$, and $Y := (y_1, y_2, \ldots, y_M)$ be two time sequences. The total cost of a warping path p between X and Y with respect to the local cost measure c is defined as $c_p(X,Y) := \sum_{l=1}^{L} c(x_{n_l}, y_{m_l})$. let p^* denote a warping path having minimal total cost among all possible warping paths. The DTW distance DTW(X,Y) between X and Y is then defined as the total cost of p^*:

$$\begin{aligned} \mathrm{DTW}(X,Y) &:= c_{p^*}(X,Y) \\ &= \min c_p(X,Y). \end{aligned} \quad (1)$$

Subsequence DTW is a variant of DTW, which applies to the case where one time sequence is much shorter than the other. Since a LightPrint is much shorter than intensity sequences in LIF maps, we apply subsequence DTW to all the possible light intensity sequences in the LIF, as shown in Fig. 6. Light intensity sequences are selected as the ones with the same direction as the directed LightPrint. However, the direction of LightPrint may be biased due to random errors, which will impact the candidate light intensity sequences. To alleviate the impact, we increase the direction range of the candidate light intensity sequences, enlarging the direction degree by θ.

Step size constraints design for accuracy Since LIFs are usually denser than LightPrints, we design the step size constraints as $p_{l+1} - p_l \in (2,1), (1,2), (1,1)$ for $l \in [1 : L-1]$ to avoid degenerations in DTW alignment, and to improve matching accuracy.

D. Localizition Based on DTW Distances

Intuitively, the light intensity segment with the minimum DTW distance should be most similar to the LightPrint. Therefore its location should be where the LightPrint is. However, we find that it is not true in many cases. There are a few light intensity segments that have similar minimum DTW distances. The sorted DTW distances is denoted as D^s with $D^s_i \le D^s_j$, for $i < j$, as shown in Fig. 7(a). We find that these light intensity segments are located regularly around light sources, where the surroundings are similar. This happens more in underground parking lot, which is regular in terms of lamp deployment, floor plan and surroundings.

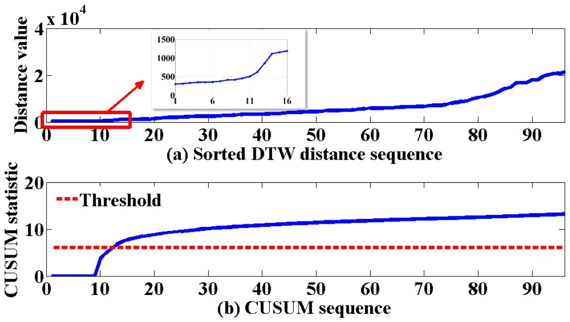


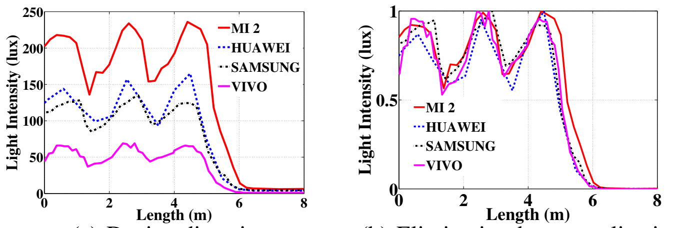
Fig. 7: K determination via CUSUM.

To improve the localization accuracy, we cluster the top K light intensity segments with similar minimum DTW distances, according to their Euclidian distances in the physical space. A cluster with the smallest average DTW distance is taken as the most similar one to the LightPrint. Locations of the cluster and the LightPrint are regarded as the same. The error distance is averaged over Euclidian distances between the real location of the LightPrint and that of each light intensity segment in the cluster. K can be determined adaptively by CUSUM (CUmulative SUM).

Adaptive determination of K via CUSUM As shown in Fig. 7(a), there is an anomaly point in the D^s sequence, which is denoted as the Kth point without loss of generality. Before K, the values are small with weak differences, whereas after K, the values increase to large ones. To detect the anomaly point, we apply widely used CUSUM algorithm [19]. Note that CUSUM assumes negative average value of the sequence, and it becomes positive after change. Therefore, without losing any statistics properties, we transfer the sequence D^s_i into another sequence $\bar{D^s}_i$ with a negative mean. Let $\bar{D^s}_i = D^s_i - a$ and $E(D^s_i) = c$, then $E(\bar{D^s}_i) = c - a$. The parameter a is set as $(1+\alpha) \times c$. It is used to produce a negative random sequence. When DTW distance increases with anomaly, $\bar{D^s}_i$ will suddenly become large positive. Let

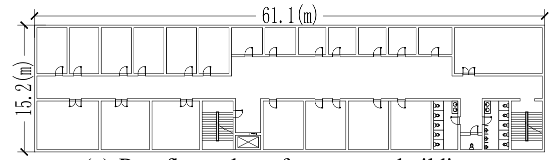
$$Z_i = \begin{cases} max(0, Z_{i-1} + D^s_i - a), & \text{if } i > 0; \\ 0, & \text{if } i = 0. \end{cases}$$

A large Z_K is a strong indication of a rapid rising of DTW distance, which can be detected using a threshold as shown in Fig. 7(b).

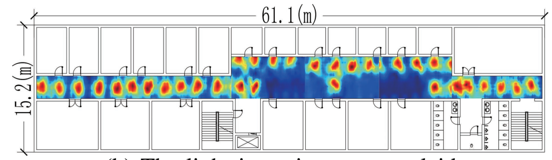


(a) Device diversity (b) Elimination by normalization

Fig. 8: Dealing with device diversity.



(a) Part floor plan of a campus building



(b) The light intensity map overlaid

Fig. 10: LIF map construction example.

E. Other Design Considerations

Exception handling To survive from wrong classification in the coarse-grained localization phase, we set a threshold δ for DTW distances by experience. If the minimum DTW distance is larger than δ, it means that none of the light intensity segments in the LIF is similar to the LightPrint. The result is fedback to the mobile client. The mobile client will encourage the user to get location again, with some suggestions. For example, walking straight for a little bit longer, and keeping the smartphone horizontal, or pointing forward, *etc.*. Note that this is not necessary, but can help to improve the localization accuracy.

Extending to Navigation Unlike localization, in navigation users usually keep walking for a long way until they arrive the destination. The size of the light intensity trace increases continuously during walks. It is impossible to match all traces against the LIF. To address the problem, we define a sliding window with a fixed size W. W is the number of samples for a light intensity trace. At the beginning, we do not start navigation until W light intensity samples are recorded. W is determined by experience, which is the number of the light intensity samples recorded at normal walk speed around 2 meters (or, 3 to 4 steps). It is also the distance that can achieve high accuracy (Sec. IV). During walks, the sliding window moves along the walk trace, and the corresponding light intensity trace with W samples is used as LightPrint.

Handling with Device Diversity Due to device diversity, light intensity measurements may be biased, meaning that phones may show different readings for a same set of light intensities. This is verified in Fig. 8(a), showing light intensities collected along the same path using different smartphones. Fortunately, the shapes of the light intensity traces are all similar for the same path. Therefore, we handle the device diversity issue with a normalization technique: both the LIF and the LightPrint are normalized by their maximum before applying DTW. The results are shown in Fig. 8(b). We can see that after normalization, the LightPrints recorded by different phones keep good consistence to each other.

IV. Implemetation and Evaluation

A. Implementation

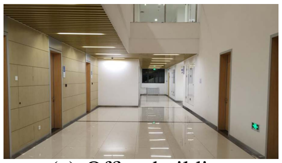
We implement the sensing function of NaviLight as an Android application on several smartphones, including Blue vivo 5, Huawei Honor 7i and MI 2, and deploy the localization and navigation algorithms at a server. To evaluate NaviLight we conduct extensive experiments in three typical indoor environments (Fig. 9): an office building in our campus, a shopping mall, and an underground parking lot. The total size of tested areas is over 1000m^2. These scenarios are different in various aspects, including area shapes, bulb types, and bulb deployment densities and regularities. We summarize the differences among these typical scenarios in Table. 9(d). All the differences make their LIFs feature diverse. Therefore we verify NaviLight in these respective scenarios.

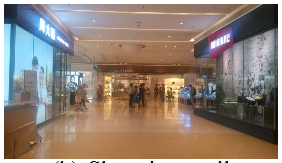
LIF Map Construction For each scenario, we build a LIF map overlaid on the floor plan as that in Fig. 10b. To build LIF maps, we first divide a whole floor area into smaller subareas according to the environment conditions (room layout, lamp types and deployment density, *etc.*). Then we further partition each subarea into grids. The grid line density complies with the sampling theory, *i.e.*, $2\times$ (the density of lamps). To make it more accurate, we add more grid lines under lamps. We only collect light intensities along the grids. Other light intensities are generated by interpolating. After interpolating, the resolution of LIF maps reaches 5cm $\times$ 5cm per pixel. It is fine-grained enough to support sub-meter accuracy localization.

B. Evaluation

Methodology We walk randomly in each scenario, and collect LightPrints during walks. We then run NaviLight to estimate their locations in LIFs, and calculate the location errors. The experiments last for 6 months. LIFs are built at the beginning, and test data are collected over the time period covered by the experiments.

We illustrate the localization accuracy of NaviLight, and how it is affected by the length of a LightPrint. Since DTW distances of the matched light intensity segments have weak discrimination due to regularities, we propose an approach to classify the top K light intensity segments with minimum DTW distances according to their spatial Euclidian distances (see Sec. III-D). The conventional method using the smallest DTW distance is denoted as MD. We compare NaviLight with MD approach. We also analyze K value distribution to see why NaviLight outperforms MD.


(a) Office building

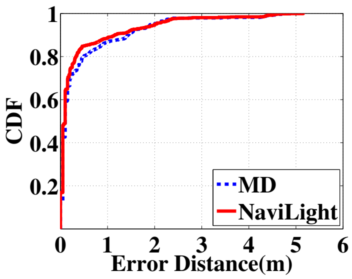

(b) Shopping mall


(c) Parking lot

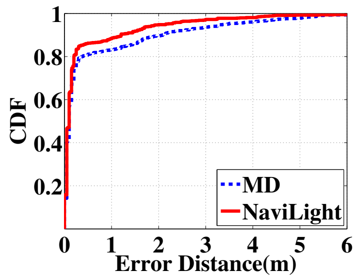
	Office	Mall	Parking
Area	625 m^2	148 m^2	260 m^2
Shape	Irregular	Irregular	Regular
Bulb	LFL,LED	LFL, CFL, LED	LFL
Number	130	38 (excl. shop light)	20
Density	1.2 – 3.0 m	1.5 – 3.6 m	3.3 – 5.4 m
Deployment	Irregular	Irregular	Regular

(d) Settings

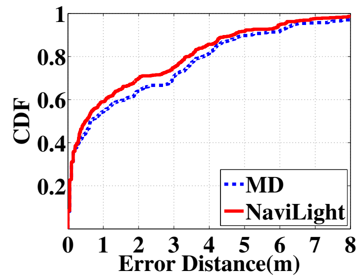
Fig. 9: Three typical experimental scenarios: an office building, a shopping mall and an underground parking lot.



(a) Office building.



(b) Shopping mall.



(c) Parking lot.

Fig. 11: Localization accuracy via LightPrint matching.

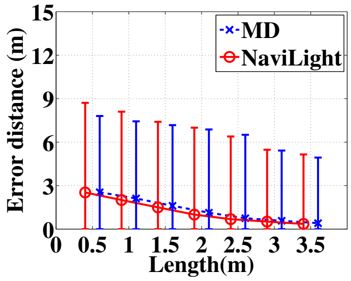
Localization accuracy The experiment results are shown in Fig. 11. It shows that NaviLight yields high accuracy for all the three environments. For the office building and the shopping mall, the 85th percentile errors are within 0.5m and 0.35m respectively, achieving sub-meter level accuracy. For the underground parking lot, the 85th percentile errors are within 3.9m, but 59% of errors are within 1.0m. Among the three scenarios, the underground parking lot is simplest and most regular, since there is only one lamp type of LFL with regular deployments, and the layout is regular too. Moreover, its separation distances between adjacent lamps are 3.3 m and 5.4 m, pretty larger than that in other scenarios. In contrast, the shopping mall is most complicated and irregular. There are 3 types of lamps and many shop lights with irregular deployments. The surroundings are diverse, including lots of decorations and walls made of various materials. Therefore the performance in the shopping mall is better than that in office building and parking lot. Although the office building is simply decorated, the lamp deployment is denser than that in the parking lot, and thus it achieves a better performance.

NaviLight always outperforms MD in all the scenarios tested. By clustering the top K light intensity segments with minimum DTW distances, NaviLight improves the localization accuracy. NaviLight achieves sub-meter level accuracy.

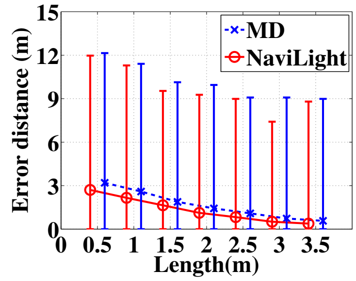
Localization accuracy vs LightPrint The spatial discrimination of a LightPrint is dependent on its length. We now examine how the length of a LightPrint impacts on the localization performance. Fig. 12 plots the localization errors in three scenarios for different lengths of LightPrints. It shows that NaviLight yields higher accuracy for longer LightPrints. The average localization errors are within 1.0 m at the LightPrint of 2.0m (only 2–3 steps) for the office building and the shopping mall; and that of the parking lot is 2.6m. However, the standard deviations at this LightPrint level are a bit larger than that at longer LightPrints. When the length of a LightPrint is about 3.0m, the localization performance achieves almost the best. The average localization errors are 0.5m, 0.5m and 1.6m for the office, mall and parking lot respectively. The performance improves very little with the LightPrint length any more. This is because longer LightPrint will result more random errors during walks. In summary, a user can get sub-meter localization service with only 2–3 steps walk in the office and shopping mall scenarios, whereas a little bit more steps for a parking lot.

K **value analysis** NaviLight achieves high accurate localization and outperforms MD, since it exploits DTW distance confidence by clustering the top K light intensity segments with minimum DTW distances. K means that there are K light intensity segments in the LIF similar to the LightPrint. The similarity is caused by the regularity of the LIF due to lamp deployments or decorations. Fig. 13 verifies this inference. We can see that the 90 percentile of K is 3 for the office and the shopping mall, whereas it increases to 6 for the parking lot. It is because there are single type of lamps and regular deployment with little decorations in the parking lot. By clustering the similar light intensity segments via their distances in physical spaces, the localization accuracy increases efficiently, as illustrated in Fig. 12.

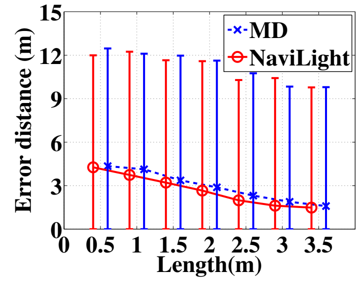
Coarse-grained localization accuracy In order to make NaviLight scalable to large indoor environments, we localize the LightPrint into one of subareas of the LIF via KNN classification before matching. Fig. 14 shows the subarea level localization accuracy with the LightPrint. When the LightPrint is 1.5 m, the 90th percentile accuracy is above 91% for all the three scenarios; it is as high as 96% for the shopping mall. The accuracies are above 95% at the LightPrint of 2.5 m. Although the accuracy is very high, it may still cause the LightPrint matching failure. Therefore NaviLight check the shortest DTW distance while matching the LightPrint. If the shortest DTW



(a) Office building.



(b) Shopping mall.



(c) Parking lot.

Fig. 12: Localization accuracy vs. LightPrint length.

distance is above a threshold, it alerts and suggests the user to walk again, and try to give an accurate location. We will improve the performance of the coarse-grained localization accuracy in the future work.

Navigation accuracy To evaluate the navigation accuracy, we walk along planed paths, recording light intensities and gyroscope sensor data. During walks, NaviLight detects direction changes and generate LightPrints with directions. The size of LightPrints is within the size of the sliding window. NaviLight estimates the location of LightPrints dynamically. We calculate the accumulated errors till the end of the path. Fig. 15 plots error distances for the three scenerios. It shows that NaviLight also performs well in navigation. The 85th percentile localization errors are within 1.6m, 2.2m and 4.3m for the office building, the shopping mall and the underground parking lot respectively. 77.3% of errors for the office are within 1.0m. There are 68.3% and 48.6% of errors within 1.0m respectively for the shopping mall and the parking lot, achieving sub-meter accuracy too.

V. Discussions and Future Work

In this section, we discuss some remaining issues and potential directions for future work.

Sunlight impact NaviLight is still in its infancy, and can work only in indoor environments without sunlight, since sunlight impacts light intensity field heavily. This is the weakest point of NaviLight. Fortunately, we find that sunlight cannot come into many indoor environments, *e.g.*, large shopping malls, supermarkets, underground parking lots and even some office buildings (especially the aisles). For example the shopping mall and the underground parking lot tested in our work. In addition, according to graphic theory [12], the sunlight can be taken as a point light source in some conditions. In future work, we will consider the sunlight impact on LIF map, and expect to make NaviLight robust in indoor environments with sunshine.

LIF construction overhead and lamp changes Site survey needs to be done from time to time to update LIF maps in order for facility changes like removing/replacing old lamps and adding new lamps. It is time-consuming and labor-intensive to maintain a large LIF map. However our approach to construct the light intensity field is pretty efficient. In addition, LIF map can also be built by crowdsourcing as in [20].

Usage diversity Light intensities might be affected by phone usage, such as phone's height and angle. However, as long as the height and the angle of the phone keep unchanged during walks, LightPrints will keep same profiles. Therefore, we can use normalization to address the usage diversity problem. In addition, if the phone is too close to a user's body, the body will block the light, especially in corridors with lamps standing in a line. The effect will be alleviated if the user carries the phone farther away from the body, and out of the body's shadow. In other scenarios with many lamps around, such as halls, shopping malls and parking lots, the effect of body block has little impact on the localization accuracy.

VI. Related work

The popularity of mobile and pervasive computing stimulates extensive research on indoor localization and navigation. Most of them leverage signals such as WiFi [21], [22], FM [23], and magnetism [24]. Here we only review the closely related works based on visible lights.

Many recent works explore visible light for localization [1]–[5], [7], [25]. However, all of them need to communicate with lights, and thus light sources are limited as LEDs. Moreover, they require location information of LEDs to be landmarks. The key technique lies in the communication method with the LED, including modulation and demodulation, *etc.*. To this end, many of them rely on extra hardwares for communication. In contrast, NaviLight can work under arbitrary light sources. It needs neither signaling nor location of the light source. Therefore it depends on the ubiquitous available and pre-collected LIFs for localization, without requiring any costumized hardware.

Little work has been done to leverage information from unmodified luminaries in indoor localization. Light matching [26] utilized position, orientation and shape information of all indoor luminaries, and models illumination intensity using an inverse-square law. Xu *et al.* propose IDyLL [6], which obtains luminary locations by detecting peaks of light intensity trace along walks. Compared with the existing works, we propose the concept of LightPrint, and implement a prototype system to verify feasibility of NaviLight for indoor localization. We hope NaviLight can shed light on the light fingerprint based indoor localization.

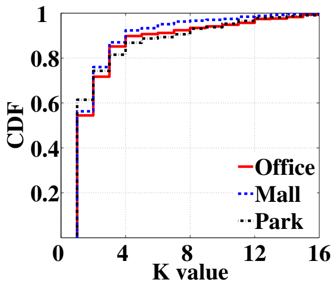


Fig. 13: K value analysis.

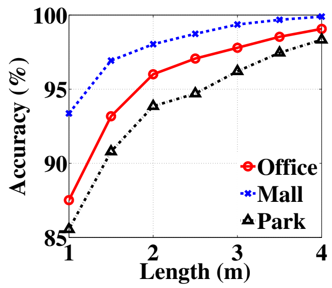


Fig. 14: Coarse-grained localization accuracy.

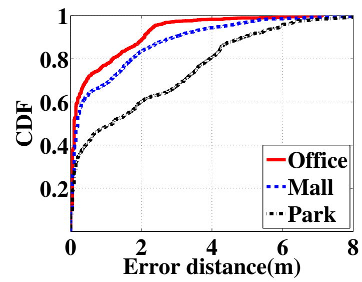


Fig. 15: Navigation accuracy.

VII. Conclusion

We studied visible light localization and navigation under arbitrary light infrastructures, and proposed an integrated framework NaviLight to achieve practical services based on pattern matching between LightPrint and LIF (light intensity field) maps. Our work is based on experimental observations that LightPrint can be used as feasible location signatures. Although our design is challenged by regularity ambiguity of LIF map and huge computational complexity due to free LightPrint, we achieved real-time navigation with sub-meter accuracy by proposing a set of mechanisms and corresponding algorithms. As far as we know, NaviLight is the first practical system for generic indoor localization and navigation under arbitrary light infrastructures.

Acknowledgement

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References

[1] K. Ye-Sheng, P. Pat, H. Ko-Jen, and D. Prabal, "Luxapose: Indoor positioning with mobile phones and visible light," in *Proc. of ACM MobiCom*, 2014.

[2] L. Li, P. Hu, C. Peng, G. Shen, and F. Zhao, "Epsilon: A visible light based positioning system," in *Proc. of NSDI*, 2014.

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

[4] J. Armstrong, Y. Sekercioglu, and A. Neild, "Visible light positioning: a roadmap for international standardization," *Communications Magazine, IEEE*, vol. 51, no. 12, pp. 68–73, 2013.

[5] N. Rajagopal, P. Lazik, and A. Rowe, "Visual light landmarks for mobile devices," in *Proc. of IEEE/ACM IPSN*, 2014, pp. 249–260.

[6] Q. Xu, R. Zheng, and S. Hranilovic, "Idyll: indoor localization using inertial and light sensors on smartphones," in *Proc. of ACM UbiComp*. ACM, 2015, pp. 307–318.

[7] B. Xie, S. Gong, and G. Tan, "Lipro: light-based indoor positioning with rotating handheld devices," *Wireless Networks*, pp. 1–11, 2016.

[8] B. P. Administration, "2015 non-residential lighting market characterization," 2015, https://www.bpa.gov/EE/Utility/research-archive/Documents/Momentum-Savings-Resources/2015_Non-Res_Lighting_Mkt_Characterization.pdf.

[9] U. D. of Energy, "2010 u.s. lighting market characterization," 2012, http://apps1.eere.energy.gov/buildings/publications/pdfs/ssl/2010-lmc-final-jan-2012.pdf.

[10] A. Gruen and D. Akca, "Least squares 3d surface and curve matching," {*ISPRS*} *Journal of Photogrammetry and Remote Sensing*, vol. 59, no. 3, pp. 151 – 174, 2005.

[11] J. H. Lambert, *Photometria*, 1760.

[12] J. J. McConnell, *Computer graphics: theory into practice*. Jones & Bartlett Learning, 2006.

[13] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE Transactions on Information Theory*, vol. 13, no. 1, pp. 21–27, January 1967.

[14] F. Li, C. Zhao, G. Ding, J. Gong, C. Liu, and F. Zhao, "A reliable and accurate indoor localization method using phone inertial sensors," in *Proc. of ACM UbiComp*, 2012, pp. 421–430.

[15] P. Zhou, M. Li, and G. Shen, "Use it free: Instantly knowing your phone attitude," in *Proc. of ACM MobiCom*, 2014, pp. 605–616.

[16] N. Roy, H. Wang, and R. Roy Choudhury, "I am a smartphone and i can tell my user's walking direction," in *Proc. of ACM MobiSys*, 2014, pp. 329–342.

[17] A. T. Mariakakis, S. Sen, J. Lee, and K.-H. Kim, "Sail: single access point-based indoor localization," in *Proc. of ACM MobiSys*, 2014, pp. 315–328.

[18] R. L. R. and J. B. H., "Fundamentals of speech recognition," 1993.

[19] M. Basseville, I. V. Nikiforov *et al.*, *Detection of abrupt changes: theory and application*. Prentice Hall Englewood Cliffs, 1993, vol. 104.

[20] A. Rai, K. K. Chintalapudi, V. N. Padmanabhan, and R. Sen, "Zee: zero-effort crowdsourcing for indoor localization," in *Proc. of ACM MobiCom*, 2012, pp. 293–304.

[21] L. Li, G. Shen, C. Zhao, T. Moscibroda, J.-H. Lin, and F. Zhao, "Experiencing and handling the diversity in data density and environmental locality in an indoor positioning service," in *Proc. of ACM MobiCom*, 2014, pp. 459–470.

[22] P. Bahl and V. N. Padmanabhan, "Radar: An in-building rf-based user location and tracking system," in *Proc. of IEEE INFOCOM*, 2000, pp. 775–784.

[23] Y. Chen, D. Lymberopoulos, J. Liu, and B. Priyantha, "Fm-based indoor localization," in *Proc. of ACM MobiSys*, 2012, pp. 169–181.

[24] Y. Shu, C. Bo, G. Shen, C. Zhao, L. Li, and F. Zhao, "Magicol: Indoor localization using pervasive magnetic field and opportunistic wifi sensing," *IEEE Journal on Selected Areas in Communications*, vol. 33, no. 7, pp. 1443–1457, July 2015.

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

[26] A. R. Jimnez, F. Zampella, and F. Seco, "Light-matching: A new signal of opportunity for pedestrian indoor navigation," in *Proc. of IPIN*, Oct 2013, pp. 1–10.