FiatLux: Fingerprinting Rooms Using Light Intensity

Nishkam Ravi and Liviu Iftode
Department of Computer Science, Rutgers University, NJ 08854
{nravi, iftode}@cs.rutgers.edu

Abstract. Indoor localization is an open problem. In this paper, we explore the possibility of fingerprinting rooms based on the intensity of light incident on a light sensor worn by the user, under static lighting conditions. We present three algorithms for fingerprinting, namely *Bayesian*, *Range-max* and *Spatial* and present experimental results for the first two. Bayesian performs better, achieving an accuracy (i.e success probability) of more than 90% when the light sensor is worn on top of a hat, and more than 80% when the light sensor is worn as a pendant. This approach does not require any infrastructure; existing light sources in rooms are used for localization.

1 Introduction

Determining user's location indoors has long been a goal of pervasive computing research. Indoor localization systems need to perform well on a number of metrics including precision, accuracy, robustness, scalability, privacy, infrastructure requirements resource requirements and non-intrusiveness. Although numerous indoor localization systems already exist, none of them scores perfectly on all the metrics, warranting further research in this field. Furthermore, different location-based services have different requirements, and it is very likely that instead of one system being globally accepted, many different systems will co-exist in the future.

Since location-based services have rather weak economic models, there is a need to design low-cost localization systems that require minimal or preferably no infrastructure to be installed in buildings in order to make bootstrapping easier. Precision and accuracy are often traded for low-cost and low-maintenance. Room-level positioning is believed to be necessary and sufficient for a number of applications. Numerous ways of achieving room-level or sub-room-level precision have been proposed. The popular ones can be classified into seven categories, based on the technology used for localization: WiFi-based, GSM-based, RF-based, Ultrasonic-based, audio-based, Bluetooth-based, and vision-based. With the exception of GSM-based and vision-based, all other approaches require specialized devices to be installed in buildings which increases the cost and decreases the chances of deployment.

GSM-based indoor localization [8] is quite effective and is claimed to be accurate as well. The main limitation of this approach is that it is hard to tell which side of the wall the user is on. As a result, a location-aware system may connect the user's phone to the wall-display in the neighboring room. GSM-based solutions make the assumption that the user has a GSM phone, while in several countries including the US, CDMA is more popular. Furthermore, a significant amount of time and effort needs to be spent on collecting training data for fingerprinting rooms.

Vision-based solutions that do not require visual tags are quite appropriate for room-level localization. Ravi et al [11] showed that user's location can be determined with high room-level accuracy, based on the what the camera-phone (worn as a pendant) "sees". One limitation of this method is that it is not robust to movement of furniture or presence of mobile objects such as human-beings that may obstruct the line-of-sight, especially in crowded buildings. Also, significant amount of time and effort needs to be spent on collecting training data.

Light has the interesting property that it does not cross walls and is omnipresent. In this paper, we explore the possibility of fingerprinting rooms based on the intensity of light incident on a light-sensor worn by the user if the lighting conditions remain constant over time. The hypothesis is that the distribution of light intensity inside a room is unique under static lighting conditions. The main advantage of this approach is that it does not require any infrastructure to be deployed, no wireless access points are needed and objects do not have to be "tagged". Already existing light sources in buildings are used for localization. In addition, it only takes around a minute to collect training data for a room, which is very efficient.

We carried out two sets of experiments for 20 rooms that we had access to in the two buildings of the Computer Science department. In the first set of experiments, the light sensor was worn on top of a hat, while in the second set of experiments, the light sensor was worn as a pendant. We experimented with two different fingerprinting algorithms. With the better algorithm, we achieved room-level precision with more than 90% accuracy when the light sensor was worn on a hat, and more than 80% when the light sensor was worn as a pendant. In real life, the user could wear the sensor either on the shoulder (similar to wearing on a hat), or as a pendant (if lower accuracy is tolerable).

Even higher accuracy can be achieved if the spatial distribution of light intensity is made use of. However, creation of spatial-fingerprints is time consuming. Also, if we imagine light sources of adjustable intensity (which are already in use) being installed in rooms, then the light intensity in every room can be set to a slightly different level, allowing for a nearly perfect room-level localization system.

The rest of the paper is organized as follows. We discuss related work in Section 2. Section 3 describes the algorithms used for localization and the data collection methodology. Experimental results are presented in Section 4. We conclude in Section 5 with directions for future work.

2 Related Work

A number of indoor positioning systems have been built. In ActiveBadge [17] an IR badge worn by the user emits a unique IR signal periodically. Sensors installed at known positions pick up the signal and update the position of the badge in a centralized database. ActiveBadge provides room level positioning and incurs significant installation and maintenance costs. Active Bat [4] provides centimeter level positioning by using ultrasound receivers, which are installed on ceilings, and ultrasound transmitters, which are carried by users/devices. Also, the cost of deployment is significant. In Cricket [9] ultrasound transmitters are installed at known coordinates to emit signals, which are received by user's mobile device to estimate location based on time-of-flight. Cricket achieves meter level positioning. It requires installation of special beacons and users have to carry special receivers.

Radar [1] operates by recording and processing signal strength information at multiple WiFi base-stations. It uses signal propagation modeling to determine user's location with 5 meters accuracy. Although no additional hardware is required, WiFi coverage is assumed. Similarly, Place Lab [6] works by listening for the transmissions of radio sources such as 802.11 access points, fixed Bluetooth devices, and GSM cell towers. A beacon database provides location information based on the IDs of beacons. PlaceLab can provide user location with upto 15 meters of accuracy. PlaceLab is a very practical, high-coverage and low-cost location determination system in that no additional hardware is required. However, presence of beacons, corresponding receivers and beacon database is assumed.

WALRUS [3] provides room-level positioning by using wireless networking and microphones. Wireless data and ultrasound pulses are generated from PCs in each room, and a PDA carried by the user listens for both signals. Ultrasound pulses are generated from speakers attached to the PC and do not carry any data. Wireless interface on the PC provides a synchronizing pulse along with information about each room. Although no additional hardware is required, WALRUS assumes the presence of a PC in each room and WiFi coverage. Similarly, Audio Location [15] determines user location by using microphones that listen to sounds made by the users themselves such as finger clicking. It is a low-cost system that achieves centimeter level accuracy. However, it assumes the presence of microphones in the environment and may not work properly in a noisy environment. The Smart Floor system [7] uses special floor tiles to identify users based on their footsteps. Although the user does not have to carry any special device, the floor needs to be instrumented with these special tiles.

GSM-based localization [8] that uses wide signal-strength fingerprints is a good solution for indoor localization because it does require any extra infrastructure and is claimed to achieve a median accuracy of five meters. The main limitation of a GSM-based approach is that it is hard to tell which side of the wall the user is on, which is crucial for several applications. A location-aware system may connect the user's phone to the wall-display in the neighboring room, which is not acceptable. GSM-based solutions make the assumption that the user has a GSM phone while in several countries including the US, CDMA is more popular. Furthermore, a significant amount of time and effort needs to be spent on collecting training data for fingerprinting rooms using GSM.

Microsoft's EasyLiving [5] project uses cameras installed in rooms to track humans using vision techniques. The cost of installing cameras in every room makes deployment difficult. Privacy is is a big issue as users are continuously *watched*. Work is being done in using camera phones as interaction devices by tagging physical objects with visual codes and using vision techniques to extract and interpret the information stored in these visual codes [13, 2, 12, 14, 16]. Localization could also be possibly achieved with this method. However, physical objects would have to be tagged.

Vision-based solutions that do not require visual tags are quite appropriate for room-level localization. Ravi et al [11] showed that user's location can be determined with high room-level accuracy, based on the what the camera-phone (worn as a pendant) "sees". One limitation of this method is that it is not robust to movement of furniture or presence of mobile objects such as human-beings that may obstruct the line-of-sight, especially in crowded buildings. Also, significant amount of time and effort needs to be spent on collecting training data.

Randall et al [10] show how solar cells in conjunction with an RFID-based localization system can be used to determine user's location. RFID is used to get a rough estimate of user's location, and solar cells are used to estimate user's displacement (i.e distance from light sources) in order to get an accurate estimate of user's location. Since solar cells are used for displacement estimation, user activity (e.g standing, walking, running) can also be estimated. Contrary to this approach, we use light sensors to fingerprint rooms and are able to determine which room the user is in without requiring another localization system.

The main advantage of our approach is that it does not require any infrastructure to be deployed, no wireleless access points are needed and objects do not have to be "tagged". Already existing light sources in buildings are used for localization. In addition, it only takes around a minute to collect training data for a room, which is very efficient.

3 Methodology

3.1 Light Illumination and Light Sensors

Light is the term used for electromagnetic radiation of frequencies in the band 4×10^{14}Hz to 8×10^{14}Hz. *Luminous flux (F)* is the measure of effectiveness of light in producing visual sensation and is directly proportional to the brightness of the light source. The *luminous intensity (I)* of a point-source is a measure of the luminous flux (F) it produces per unit solid angle (Ω), and is defined as the ratio $dF/d\Omega$. Finally, *illumination (E)* is a measure of the luminous flux (F) falling per unit area (A) of a surface (e.g a light sensor) and is defined as the ratio dF/dA. Illumination is measured in *lux*, and is related to intensity I by the expression: $E = Icos\varphi/r^2$, where r is the distance of the surface from the

Fig. 1. A Light Sensor

light-source and φ is the angle the normal to the surface makes with the incident radiation. While intensity is a property of the light source, illumination depends on the distance of the surface from the light source and its orientation.

A light sensor measures illumination, which is intuitively the amount of light energy incident per unit area of the light sensor. Illumination is measured in *lux* and is directly proportional to the intensity of the light source. Light sensors are typically semi-spherical in shape. Figure 1 shows a typical light-sensor.

3.2 Fingerprinting and Localization Algorithms

The amount of light energy incident on a light sensor depends on the intensity of the light sources in the room as well as reflection from walls and objects inside the room. While light illumination at a particular location inside a room may be the same as that at another location in a different room, the distribution of light illumination values in rooms are quite distinct. The problem of identifying which room the user is in based on a set of light illumination values, can be formulated as a classification problem for which fingerprints of rooms need to be created. We describe three algorithms for fingerprinting and identifying rooms.

Bayesian fingerprinting. In Bayesian fingerprinting, the light illumination values of a room collected during the training phase are discretised into a number of intervals. A histogram is then obtained by counting the number of points that lie in each interval. Each point corresponds to the value of light illumination at a certain location in the room. The height of an interval is, therefore, directly proportional to the number of locations in the room with light illumination value in that interval. In order to create such a histogram, the data collector must spend equal amount of time at every location in the room during the data collection phase. Figure 2 shows the Bayesian fingerprints (or histograms) for four rooms. It is evident from the figure that the fingerprints are quite distinct. Note that this algorithm does not take into account the spatial distribution of light illumination in the room.

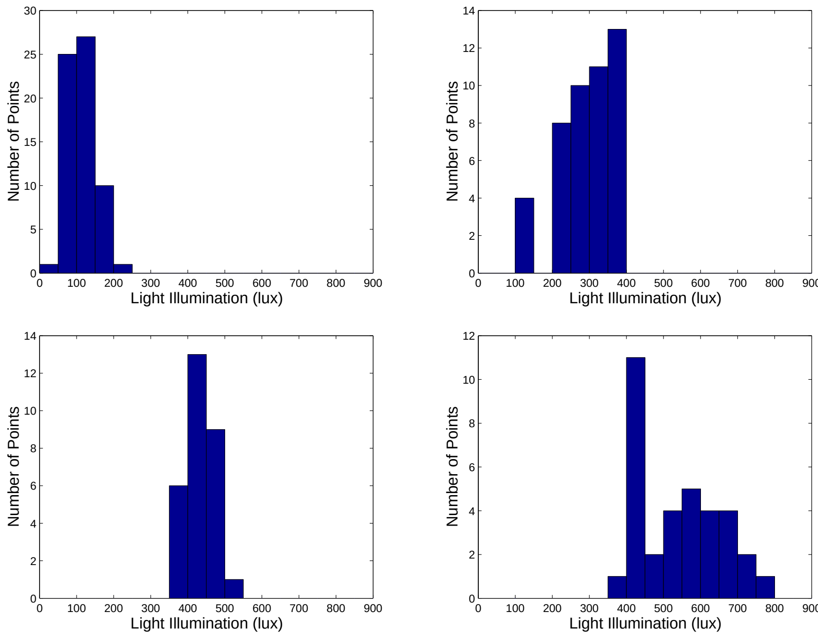

Fig. 2. Bayesian fingerprints (histograms) for four rooms

Bayesian localization. During the testing phase, when a new set of light illumination values s is obtained, Bayesian localization finds the room R that maximizes the probability $P(R|s)$, i.e $\arg\max_R P(R|s)$. $P(R|s)$ denotes the probability that the points in set s have been sampled from room R. Applying Bayes rule, we get: $\arg\max_R P(R|s) = \arg\max_R P(s|R).P(R)/P(s) = \arg\max_R P(s|R)$, assuming $P(R_1) = P(R_2).. = P(R_n)$.

We know that $\arg\max_R P(s|R) = \arg\max_R \mathit{\Pi}_i\{P(a_i|R)|a_i \in s\}$. Probability of sampling a point from a room is directly proportional to the height of the histogram interval in which the point falls: $P(a_i|R) = h_R(a_i)/\sum_i h_R(a_i)$, where h_R denotes the histogram for room R, and $h_R(a_i)$ denotes the height of the interval in which a_i falls. From here we obtain, $\arg\max_R P(R|s) = \arg\max_R \prod_i (h_R(a_i)/\sum_i h_R(a_i))$. Intuitively, the probability that a set of points s has been sampled from room R is directly proportional to the product of the heights of the histogram intervals in which the points in s fall.

Range-max fingerprinting. In Range-max fingerprinting, only the minimum and maximum values of light illumination obtained for a room during the training phase are retained. The fingerprint of a room is given by the tuple $\{min, max\}$, which denotes the range of light illumination values in that room. Figure 3 shows the Range-max fingerprints for six rooms.

[0,250]	[100,400]	[350,550]	[350,800]	[50,150]	[100,600]

Fig. 3. Range-max fingerprints for six rooms

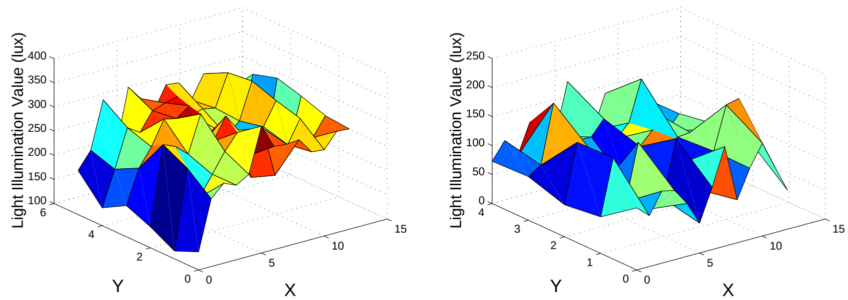

Fig. 4. Spatial fingerprints for two rooms

Range-max localization. During the testing phase, when a new set of light illumination values s is obtained, the Range-max localization algorithm finds the room R which minimizes the quantity $abs(max(R) - max(s))$ and for which $min(R) \leq min(s) \leq max(s) \leq max(R)$. Quantities $min(R)$, $max(R)$ are the minimum and maximum values of light illumination for room R as obtained from the fingerprint. Quantities $min(s)$, $max(s)$ are the minimum and maximum values of light illumination in set s. Intuitively, this algorithm assumes that every room has a unique *max* value, and that the range and the *max* value together can be used to identify a room.

Spatial fingerprinting. The two algorithms described above do not make use of the spatial distribution of light illumination inside a room. A spatial distribution is a map from location (x, y) to a light illumination value. Figure 4 shows the spatial distribution of light illumination for two rooms, which also serve as the fingerprints for the rooms.

Spatial localization. During the testing phase, when a vector of light illumination values v is obtained, the Spatial-match algorithm searches for the room which minimizes the quantity $|f - v|$, where f is the Spatial fingerprint of the room represented as a 2-dimensional vector of light illumination values. Intuitively, this algorithm tries to fit a strip of light illumination values represented by vector v on the surface of the spatial curve. The room corresponding to the curve that fits the best is returned as the location of the user.

Fig. 5. Left: light sensor on a hat. Right: light sensor as a pendant

Fig. 6. Apparatus used for data collection: a light sensor, a light meter and a laptop (optional)

Unlike the previous two fingerprinting techniques, construction of Spatial fingerprints is time-consuming and tedious. Also, the Spatial-match algorithm is quite resource-intensive. However, Spatial fingerprints can be much more effective in correctly identifying the room as compared to Bayesian and Range-max.

3.3 Data Collection

We collected light illumination measurements in two office buildings, which belong to the Department of Computer Science at Rutgers University. We only had access to the corridors and rooms on the third floors of these two buildings. In all, we collected data for 19 rooms and the corridor (henceforth 20 rooms). All these rooms have static lighting conditions.

We collected two separate datasets– one in which the light sensor was worn on top of a hat (as shown in Figure 5(left)) and the other in which the light sensor was worn as a pendant (as shown in Figure 5(right)). When the light sensor is worn as a pendant, lower accuracy can be expected because the user's body obstructs and affects the amount of light energy incident on the light sensor. For either experiment, it only takes a minute to collect data for a room, and a total of of half-an-hour to collect data for all the rooms. We constructed multiple such datasets over a time-period of a week, varying the distance of the light sensor from the ground to account for varying user heights. For this, we varied the length of the string holding the light sensor when it is worn as a pendant, and placed a cushion underneath the light sensor when it is worn on top of a hat. These datasets were mixed; some were used for training, and the others were used for testing.

For collecting training data, the user walks around the entire room at slow constant speed wearing the light sensor. The light sensor is connected to a light meter (Figure 6) which records the readings of the light sensor in *lux*. The light meter is in turn connected to a laptop which logs the data. Using the laptop is optional; the light meter itself is capable of logging the data. The probe-frequency can be varied– we chose 0.5 second for our experiments.

The training data is processed to obtain fingerprints using the algorithms described before. We experimented with Bayesian and Range-max algorithms. Construction of Spatial fingerprints requires the spatial coordinates (corresponding to every light reading) to be recorded during the data collection phase, which is tedious and time-consuming. Therefore, we did not experiment with Spatial fingerprints.

For collecting testing data, the user walks through the rooms and corridors at normal walking speed, stopping at certain locations periodically to imitate real-life mobility. The data is then pre-processed using two data filters. The first filter fragments the dataset into smaller pieces, where each piece contains the data of a room. For this, the filter looks for jumps in the light intensity readings, which correspond to the user exiting/entering a room. The second filter discards contiguous repeated readings which correspond to the user standing at a location. This is necessary for the Bayesian algorithm to work.

4 Evaluation

The goal of our experiments was to test the following hypothesis: *it is possible to determine which room the user is in if they are wearing a light sensor*. For testing this hypothesis, we test the accuracy of the two fingerprinting/localization techniques as described in Section 3.2, namely Bayesian and Range-max, on two different datasets: one in which the light sensor is worn on top of a hat, and the other in which the light sensor is worn as a pendant. We also test the scalability of these techniques by varying the number of rooms from 2 to 20. The ability to tell between 20 rooms or less is good enough for most applications if we assume that indoor localization solutions would typically work in a hierarchical fashion, i.e identify the building, identify the floor, identify the room. Our experiments were carried out in buildings with static lighting conditions (i.e no windows). Under varying lighting conditions, it would be necessary to construct multiple fingerprints for different times of the day in order to account for the effect of sunlight.

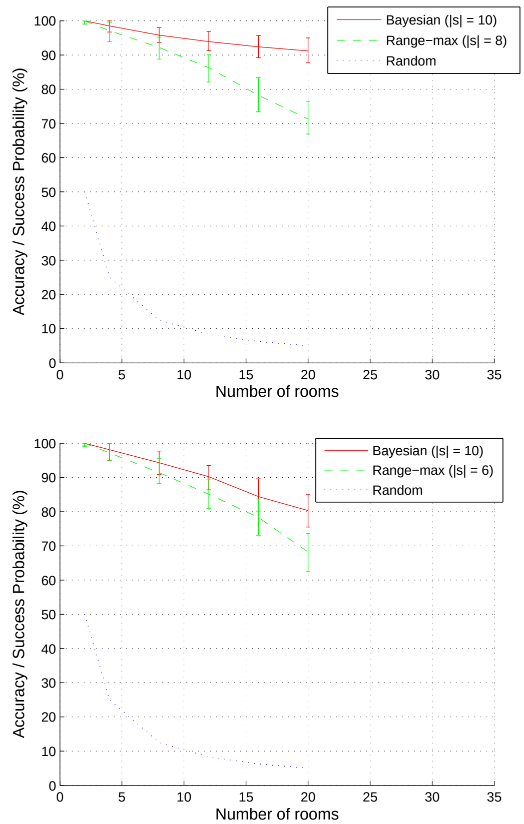

Fig. 7. Localization accuracy/success probability of Bayesian and Range-max as a function of the number of rooms. The light sensor is worn on top of a hat (top) and as a pendant (bottom).

Training and testing datasets are collected and stored separately. Training data is processed to obtain fingerprints for rooms using Bayesian and Range-max fingerprinting algorithms. Testing data is pre-processed to separate out light measurements for different rooms, and eliminate contiguous repeated readings. The testing data corresponding to a particular room is then fed into the two localization algorithms. Both the algorithms pick a contiguous set of points s starting at a random position in the dataset, which is then matched against the fingerprints as described in Section 3.2. This is repeated for all the rooms 100 times.

Localization accuracy would depend on $|s|$, which represents number of light illumination readings needed to localize the user. If the time interval between two consecutive light illumination readings is t, then the localization latency is

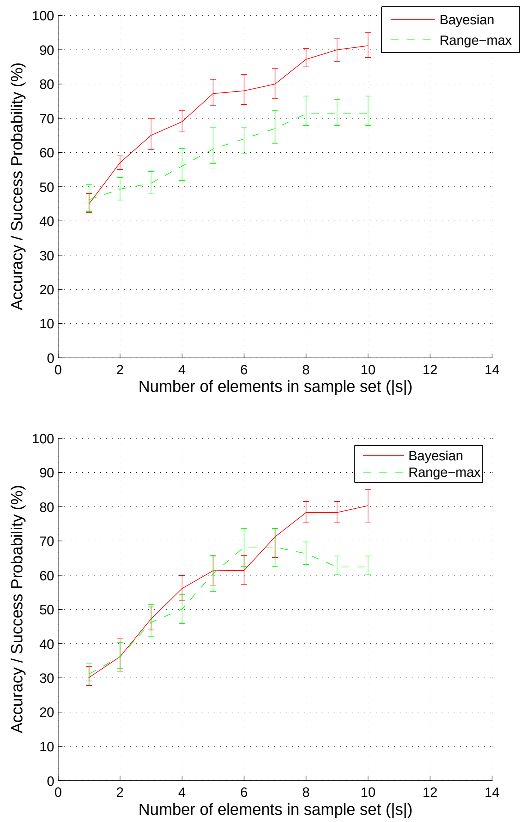

Fig. 8. Localization accuracy of Bayesian and Range-max as a function of sample set size ($|s|$) when number of rooms $= 20$. The light sensor is worn on top of a hat (top) and as a pendant (bottom).

given by $t|s|$. In our case, $t = 0.5$ second. Higher the value of $|s|$, higher the localization latency.

Figure 7 shows the localization accuracy of the two algorithms as a function of the number of rooms. The graph on the top shows the performance of the algorithms when the light sensor is worn on top of a hat, with $|s| = 10$ and $|s| = 8$ for Bayesian and Range-max respectively. The average accuracy of Bayesian for 20 rooms is 91.2% and that of Range-max is 71.6%. The bottom graph shows the localization accuracy of the two algorithms when the light sensor is worn as a pendant, with $|s| = 10$ and $|s| = 6$ for Bayesian and Range-max respectively. The average accuracy of Bayesian for 20 rooms is 80.3% and that of Range-max is 68.1%. Any sensible localization algorithm should do better than *Random*, which determines user's location by randomly picking a room.

Figure 8 shows the localization accuracy of the two algorithms for 20 rooms, as a function of $|s|$. The graph on the top corresponds to the case when the light sensor is worn on top of a hat. Bayesian attains peak accuracy when $|s| = 10$, while Range-max attains peak accuracy when $|s| = 8$. The bottom graph corresponds to the case when the light sensor is worn as a pendant. Bayesian attains peak accuracy when $|s| = 10$ in this case, while Range-max attains peak accuracy when $|s| = 6$. As mentioned before, lower value of $|s|$ implies lower localization latency.

The localization accuracy is lower when the light sensor is worn as a pendant because the user's body affects the amount of light energy incident on the light sensor. Bayesian consistently outperforms Range-max. However, Range-max requires a lower value of $|s|$ (hence lower localization latency) to reach its peak localization accuracy. Also, Range-max is independent of the amount of time the user spends at a particular location. For Bayesian, filtering needs to be carried out.

We believe that higher accuracies can be obtained with Spatial fingerprints at the cost of higher data collection time. We plan to experiment with Spatial fingerprints in the near future.

Discussion. Although it is easy to integrate light sensors into garments (e.g user's shoulder) or hang them around the neck, it is worth eliminating the need for wearing a light sensor completely. The purpose of a light sensor is to measure light illumination. Can light illumination be measured using a camera phone, which users already carry? We are currently investigating this possibility. If successful, it would be interesting to see if illumination-based localization can be combined with image-based localization [11].

In addition to performance metrics (such as accuracy), using *performance/cost* metrics may provide additional insight into the effectiveness of a localization system. One example is *accuracy/training-effort*, where training effort could be quantified as the time that needs to be spent in collecting training data for fingerprinting a room. Other such metrics could be defined, such as *precision/cost-of-infrastructure* or *coverage/resource-requirements*.

5 Conclusions

In this paper, we showed that it is possible to fingerprint rooms using light illumination values under static lighting conditions. We presented three algorithms for fingerprinting rooms and evaluated two of them, namely Bayesian and Range-max. With Bayesian, we could achieve more than 90% accuracy when the light sensor is worn on top of a hat and more than 80% accuracy when the light sensor is worn as a pendant. It takes around a minute to collect data for a room which is very efficient compared to other fingerprinting techniques. Our experiments were carried out in buildings with static lighting conditions (i.e no windows). Under varying lighting conditions, it would be necessary to construct multiple fingerprints for different times of the day in order to account for the effect of sunlight.

We plan to experiment with Spatial fingerprints in the near future, which are expected to give higher accuracies at the cost of increased effort in data collection. We also plan to evaluate our hypothesis under varying lighting conditions by constructing multiple sets of fingerprints corresponding to different times of the day. We are also investigating the possibility of measuring light illumination directly using a camera, with the goal of replacing the light sensor with a camera phone.

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