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Indoor Localization using Solar Cells

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***Abstract*—The development of the Internet of Things (IoT) opens the doors for innovative solutions in indoor positioning systems. Recently, light-based positioning has attracted much attention due to the dense and pervasive nature of light sources (e.g., Light-emitting Diode lighting) in indoor environments. Nevertheless, most existing solutions necessitate carrying a high-end phone at hand in a specific orientation to detect the light intensity with the phone's light sensing capability (i.e., light sensor or camera). This limits the ease of deployment of these solutions and leads to drainage of the phone battery. We propose *PVDeepLoc*, a device-free light-based indoor localization system that passively leverages photovoltaic currents generated by the solar cells powering various digital objects distributed in the environment. The basic principle is that the location of the human interferes with the lighting received by the solar cells, thus producing a location fingerprint on the generated photocurrents. These fingerprints are leveraged to train a deep learning model for localization purposes. *PVDeepLoc* incorporates different regularization techniques to improve the deep model's generalization and robustness against noise and interference. Results show that *PVDeepLoc* can localize at sub-meter accuracy for typical indoor lighting conditions. This highlights the promise of the proposed system for enabling device-free light-based localization systems.**

***Index Terms*—solar panels, deep learning, indoor localization, device-free localization**

I. Introduction

The current advances in the sensing capabilities of IoT devices open the door for the next generation of human-centric applications [1]–[14]. Accurate energy-efficient indoor localization comes on top of these applications. While GPS has mostly solved the localization problem in outdoor scenarios, it cannot work indoors due to the absence of the line of sight to reference satellites. Therefore, industry and academia have been devoting immense effort to find a pervasive indoor positioning system.

WiFi-based localization has been one of the main indoor localization approaches due to the widespread use of WiFi access points (APs) [4]–[7]. However, this solution suffers from practical issues such as wireless channel dynamics, fading, interference, and environmental noises that lead to unstable performance. More recently, cellular signals have been used for indoor tracking [8]–[14]. These systems are designed to map the received signal strength from the cell towers covering the area of interest to the corresponding user location. Unlike WiFi-based networks, cell towers are located outside buildings transmitting long-range signals. Therefore, the received signals are noisy and highly affected by the sensitivity of the measuring device (i.e., cell phone) [8], [11], [12].

Light-emitting diodes (LEDs) is a new lighting technology offering long lifetime and energy-saving. As LEDs are often deployed at a much higher density compared to WiFi APs, light-based localization can potentially achieve higher localization accuracy. Current light-based localization techniques [15], [16] are designed to locate the user based on the light intensity received by the user smartphone. However, leveraging the user smartphone limits its wide adoption to only users with high-end phones (i.e., equipped with light sensor or camera). Moreover, even with the availability of such high-end phones, the localization system cannot work when the phone is not exposed to the light source (e.g., the phone is in the user's pocket or bag). Additionally, the diversity of smartphones, e.g., the sensor sensitivity, sensor placement, and sampling rate, leads to a significant drop in the localization performance when the testing phone is different from the ones used in the calibration phase [8]. Finally, continuous light-sensing leads to rapid battery drainage, especially with phones powered by small batteries.

Recently, there has been a trend of fitting many indoor Internet of Things (IoT) devices with solar cells to extend their battery life or enable completely battery-free operation [17]. Inspired by this, we propose *PVDeepLoc*, a novel device-free and energy-free light-based indoor localization system that passively leverages photovoltaic currents generated by the solar cells distributed in the environment. The basic principle is that the location of the human interferes with the lighting received by the solar cells, thus producing a location fingerprint on the generated photocurrents. The fingerprints collected at pre-defined reference locations are used for train-

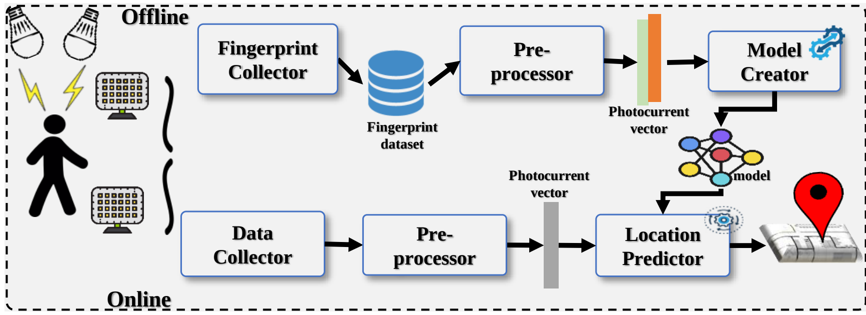

Fig. 1. The architecture of the *PVDeepLoc* system.

ing an efficient deep learning-based localization that learns the complex relationship between the photocurrent measurements of the installed solar cells and the user location. Moreover, *PVDeepLoc* employs different model regularization techniques to increase the system generalization ability and select the model's configurations optimally.

The rest of the paper is structured as follows. Section II introduces the detailed implementation and discusses the role played by each module of the proposed *PVDeepLoc* system. Section III validates *PVDeepLoc* performance with the experimental evaluations. Finally, we conclude the paper in Section IV.

II. The *PVDeepLoc* System

Fig. 1 shows the *PVDeepLoc* system architecture. *PVDeepLoc* works in two phases: an offline training phase and an online tracking phase. During the offline phase, the area of interest is partitioned into uniform virtual grids (i.e., have equal sizes). Then, the photocurrent measurements corresponding to the received light are obtained while the user is located at an arbitrary grid in the environment by the solar cells and recorded. The obtained readings are forwarded to the Pre-processor module to prepare consistent length feature vectors of photocurrent measurements enabling traing a localization model. Next, the Model Creator module constructs and trains a deep neural network while also selecting the optimal parameters for the model with provisions to avoid over-fitting. Finally, the optimal model is then saved for later use by the online Location Predictor module.

During the online phase, the user is at an unknown location while the solar cells receive light intensities from the light sources in the area of interest. The photocurrent feature vector is obtained the Pre-processor module. Finally, the Location Predictor module feeds the processed input vector to the localization model constructed in the offline phase to estimate the likelihood of the user being at any grid of the already defined ones at the offline phase.

A. The pre-processor module

This module runs during both the offline and online phases. It processes the measured photocurrent values from the installed solar cells. Specifically, the Pre-processor forms the photocurrent values in a feature vector (where each entity

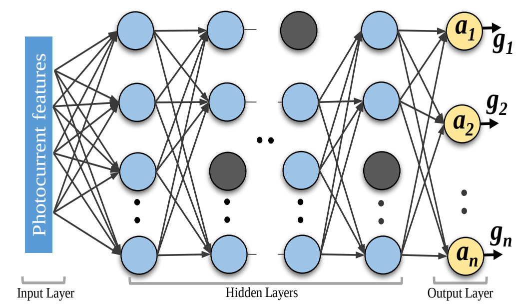

Fig. 2. Network structure. The input is the photocurrent feature vector and the output is the probability distribution for different reference grids. Grey-shaded neurons represent examples of temporarily dropped out neurons.

represents a reading from a corresponding solar cell) that fit the input length of the localization model. Then, the feature vector is re-scaled to the range of $[0, 1]$ due to the neural network's sensitivity to the input scale. Finally, to handle the noise that may be accompanied to the received light due to transient additional light or environment changes, *PVDeepLoc* employs the data augmentation framework proposed in [18] and outlier removal [19], [20]. The framework generates synthetic data from samples collected over a short-term that reflect the typical variation in measurements. It offers an additional advantage of combating the possible bias problem which may occur due to training with a small amount of data and affect the model generalization ability.

B. The localization model creator

This module is responsible for training a deep localization model and finding its optimal parameters. The selected model will be used during the online phase by the *Location Predictor* module to provide an estimate for the user location. *PVDeepLoc* employs a deep fully-connected neural network due to its hierarchical representational ability, enabling the learning of complex patterns [21].

1) The network architecture: Fig. 2 shows our deep network structure. We construct a deep fully connected neural network consisting of cascaded hidden layers of nonlinear processing neuronal units. We use the hyperbolic tangent function (tanh) as the activation function for the hidden layers due to its non-linearity, differentiability (i.e., having stronger gradients and avoiding bias in the gradients), and consideration of negative and positive inputs [22]. The network's input layer is a vector of length k representing the photocurrent feature vector. The output layer consists of a number of neurons corresponding to the number of reference grids of the area of interest that is defined by the simulator. This network is trained to operate as a multinomial (multi-class) classifier by leveraging a Softmax activation function in the output layer. This leads to a probability distribution for the expected grids given an input difference vector.

During the offline phase, the ground-truth probability label vector $P(a_i) = [p(a_{i1}), p(a_{i2})...p(a_{in})]$ is formalized using one-hot-encoding. This encoding has a probability of 1 for the correct reference grid and 0 for others. The model is trained using the Adaptive Moment Estimation (Adam) optimizer to minimize the mean cross-entropy between the estimated output probability distribution $P(a_i)$ and the one-hot-encoded vector g_i.

2) Preventing over-fitting: To increase the model robustness and further reduce over-fitting, *PVDeepLoc* employs two regularization techniques: First, we use dropout regularization during the network training (Fig. 2). We also adopt early stopping regularization method to automatically stop the training process at an optimal point in time when the performance improvements are no longer gained.

C. Online phase

This phase aims to locate the user in real-time, after deploying the system, using the measured light intensities from the installed solar cells in the area of interest. This can be done by calculating the corresponding photocurrent vector as a feature vector as described previously. Thereafter, this vector is fed to the trained localization model obtained to estimate the user location as one of the grids defined at the configuration phase. The grid g^* with the maximum probability given the feature vector (c) is selected. That is, we want to find:

$$g^* = \underset{r}{\operatorname{argmax}}[P(g|c)] \tag{1}$$

We implemented our deep learning-based training using the Keras learning library on top of the Google TensorFlow framework.

III. Proof-of-concept Implementation

A. Experimental Setup

In this section, we describe the data collection setup in a real room that spans an area of $2m \times 3m$ in a residential building (denoted experimental testbed). The testbed is equipped with *four* vertically installed solar cells at the four walls of the rooms, as shown in Fig. 3. The figure shows the 3D coordinate of the considered cells. Each solar cell has 15.5% efficiency with dimensions: length, width and depth of 10cm, 7cm and 0.15cm, respectively. The room is illuminated with a chandelier of 8 lamps of 40 watt each, i.e., 450 lumens. This light source is hung in the center of the room's ceiling at the height of 1.9m from the floor. The experiment area is uniformly partitioned into 24 different grids with $0.5m$ spacing. The data is collected while the user stands at the center of each grid cell (i.e., reference points).

TABLE I
Default parameters values used in the evaluation.

Parameter	Range	Default
Learning rate	0.0001 - 0.2	0.001
Dropout rate (%)	0 - 90	5
Early stopping patience	1-100	40
Number of hidden Neurons	20 - 1000	220
Number of layers	2 - 30	6
Number of training samples per grid	1 - 640	640

TABLE II
The localization errors of the proposed system.

Min	25^{th} Perc.	$Median$	75^{th} perc.	$Avg.$	Max
0.01	0.29	0.63	1.16	0.71	1.81

For capturing the photocurrent reading from a solar panel, we connected the solar panel to an analog to digital converter (ADC) whose output is fed to a Raspberry Pi (RPI) module. The measurements are recorded using our Python implementation, which sends an HTTP request to the four installed RPIs to get the response of photocurrent readings from their connected solar panels. These readings are aggregated into one sample stored in our fingerprint database. We collected 50 samples of photocurrent readings while the user was standing at the center of each reference grid. To enable the effective adoption of the deep learning model, the number of samples captured at each grid is increased to 400 using the proposed data augmentation methods (Section II-A).

B. Experimental results

Table II summarizes how *PVDeepLoc* performs in the considered testbed. Specifically, the *PVDeepLoc*'s localization performance is evaluated by calculating the Euclidean distance error between the ground-truth location and the estimated user location. The reported results in the table confirm the good performance of the system achieving as low as only $0.01m, 0.29m, 0.63m, 0.71m, 1.16m$ and $1.8m$ for the minimum, 25^{th} percentile, 50^{th} percentile, average, 75^{th} percentile and maximum (100^{th} percentile), respectively. This confirms the validity of *PVDeepLoc* as an accurate indoor localization system for intelligent environments.

1) Robustness to density variation of solar cells: In this section, we study the robustness of the proposed system when fewer solar cells are considered in a real-world testbed. Fig. 4 shows the effect of varying the density of the solar cells on the *PVDeepLoc* localization accuracy. For this, we randomly removed solar cells from a total of 4 solar cells installed in the area of interest. The figure shows that the more solar panel available, the richer input information to the model and thus a better localization accuracy. However, even with a density as low as only two cells, *PVDeepLoc* can achieve an accurate room-level localization with less than 2m median error. This is due to the light perturbation caused by the room's user presence, which can be measured by the installed few solar cells.

IV. Conclusion

We presented *PVDeepLoc*, an accurate and robust device-free indoor localization system that uses photocurrent measurements of solar cells to localize users passively without

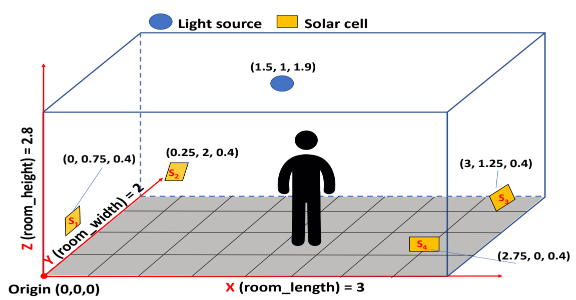

Fig. 3. The experimental setup of the real testbed.

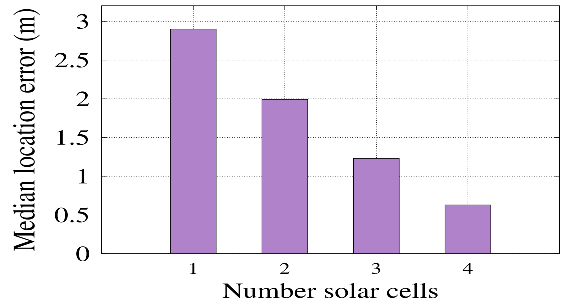

Fig. 4. Effect of changing the number of the considered solar panels.

requiring users to wear or carry any device. *PVDeepLoc* trains a deep neural network to estimate the fine-grained user location. The system employs different regularization techniques to enable the deep network to generalize and avoid over-fitting, leading to a more stable model in the case of unseen/noisy data. We evaluated *PVDeepLoc* in a challenging real-world testbed. The results show that *PVDeepLoc* comes with a median localization accuracy of more than 0.63m.

Currently, we are extending the system in different directions, including exploring more advanced neural networks to improve the accuracy with fewer and heterogeneous solar panels, studying the variation in number and type of light sources including dimmable lights and outdoor light coming in via windows, improving the system robustness against environmental changes (e.g., furniture) and variation in reflectivity of different objects as well as investigating the effect of ambient human activities and tracking multiple subjects.

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