Singapore Management University

Institutional Knowledge at Singapore Management University

Research Collection School Of Computing and Information Systems | School of Computing and Information Systems

11-2022

Photovoltaic cells for energy harvesting and indoor positioning

Hamada RIZK

Dong MA
Singapore Management University, dongma@smu.edu.sg

Mahbub HASSAN

Moustafa YOUSSEF

Follow this and additional works at: https://ink.library.smu.edu.sg/sis_research

Part of the Artificial Intelligence and Robotics Commons, and the Databases and Information Systems Commons

Citation

RIZK, Hamada; MA, Dong; HASSAN, Mahbub; and YOUSSEF, Moustafa. Photovoltaic cells for energy harvesting and indoor positioning. (2022). *Proceedings of the 30th International Conference on Advances in Geographic Information Systems, Seattle, Washington, USA, 2022 November 1 - 4*. 1-4.
Available at: https://ink.library.smu.edu.sg/sis_research/7584

This Conference Proceeding Article is brought to you for free and open access by the School of Computing and Information Systems at Institutional Knowledge at Singapore Management University. It has been accepted for inclusion in Research Collection School Of Computing and Information Systems by an authorized administrator of Institutional Knowledge at Singapore Management University. For more information, please email cherylds@smu.edu.sg.

Photovoltaic Cells for Energy Harvesting and Indoor Positioning

Hamada Rizk
Osaka University, Japan
Tanta University, Egypt
hamada_rizk@f-eng.tanta.edu.eg

Dong Ma
Singapore Management University
Singapore
dongma@smu.edu.sg

Mahbub Hassan
University of New South Wales
Sydney, Australia
mahbub.hassan@unsw.edu.au

Moustafa Youssef
AUC & Alexandria University
Cairo, Egypt
moustafa-youssef@aucegypt.edu

ABSTRACT

We propose *SoLoc*, a lightweight probabilistic fingerprinting-based technique for energy-free device-free indoor localization. The system harnesses photovoltaic currents harvested by the photovoltaic cells in smart environments for simultaneously powering digital devices and user positioning. The basic principle is that the location of the human interferes with the lighting received by the photovoltaic cells, thus producing a location fingerprint on the generated photocurrents. To ensure resilience to noisy measurements, *SoLoc* constructs probability distributions as a photovoltaic fingerprint at each location. Then, we employ a probabilistic graphical model for estimating the user location in the continuous space. Results show that *SoLoc* can localize the user at sub-meter accuracy in a real indoor environment.

CCS CONCEPTS

• **Networks** → **Location based services**; • **Human-centered computing** → *Ubiquitous and mobile computing*;

KEYWORDS

photovoltaic-based localization, deep learning, indoor localization, device-free localization, energy-free localization

ACM Reference Format:
Hamada Rizk, Dong Ma, Mahbub Hassan, and Moustafa Youssef. 2022. Photovoltaic Cells for Energy Harvesting and Indoor Positioning. In *The 30th International Conference on Advances in Geographic Information Systems (SIGSPATIAL '22), November 1–4, 2022, Seattle, WA, USA.* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3557915.3560952

1 INTRODUCTION

Indoor positioning has been a hot topic in both academia and industry to find an alternative system for GPS in indoor settings. Therefore, various technologies have been proposed to realize this and meet the increasing demand for indoor location-based services [1, 7, 22, 28, 29, 33, 34]. For instance, WiFi has been widely used for indoor positioning due to the availability of WiFi access points (APs) [1, 7, 22, 28, 29, 34]. Different signals, e.g., channel state information (CSI) [34], Received Signal Strength Indicator (RSSI) [1, 7, 28], and Round Trip Time (RTT)[22] have been used. However, WiFi suffers from issues that affect real deployments in practice such as wireless channel dynamics, fading, interference, and environmental noises; leading to unstable performance.

In the era of the Internet of Things (IoT) and sustainability, billions of devices are aimed to be connected with a low (or zero) energy consumption profile [36]. Therefore, we are witnessing more emerging technologies that are more attractive [14], including cellular, Zigbee, Light, LoRa, backscatters, etc. Cellular signals have been recently adopted for indoor positioning [2, 18–21, 24–27, 30, 31] due to its low energy consumption profile. Cellular-based systems are designed to map the long-range signals from the covering base stations to the corresponding user location inside the building. However, the received signals are noisy due to the long propagation range [20]. ZigBee is an IEEE 802.15.4-based technology of bidirectional wireless communication of short distance and low power consumption. However, ZigBee is not a favorable option due to the lack of support by the majority of most commercial on-the-shelf devices.

Light-emitting diodes (LEDs) are a new lighting technology offering a long lifetime and energy-saving light emission source. LEDs often exist with high density compared to WiFi APs. Additionally, light sensors are mainly used to sense the position and direction of the light emitters and thus estimate the user's location. This can be realized using current light-based localization measuring the light intensity received by the user's smartphone equipped with a light sensor or camera, as in [10, 37]. Nevertheless, these techniques are used to pinpoint devices carried by users, i.e., called *device-based techniques*, which limits the widespread adoption of such solutions. For example, using LEDs for localization introduces a number of hardware challenges, e.g., the device sensitivity to the incident light, the sensor type and form factor, the sensor placement and orientation, and sampling rate [5]. Besides, device-based approaches cannot be a suitable solution for various applications such as intrusion detection and elderly tracking, etc. Additionally, all the aforementioned techniques require continuous sensing that consumes the battery, especially with battery-restricted devices. This raises the need for developing the next generation of indoor positioning systems that are not only device-free but also energy-efficient.

Permission to make digital or hard copies of part or all of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for third-party components of this work must be honored. For all other uses, contact the owner/author(s).
SIGSPATIAL '22, November 1–4, 2022, Seattle, WA, USA
© 2022 Copyright held by the owner/author(s).
ACM ISBN 978-1-4503-9529-8/22/11.
https://doi.org/10.1145/3557915.3560952

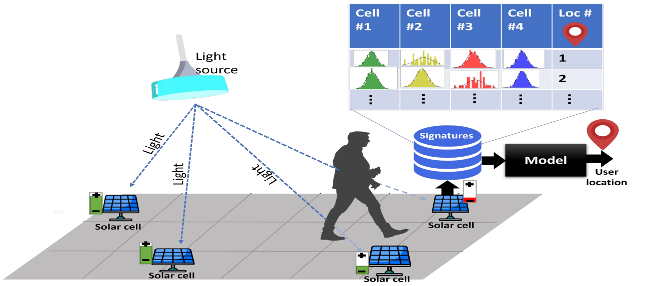

Figure 1: *SoLoc* concept and basic idea.

Towards this end, a promising solution is to leverage energy harvesters to convert ambient energy into electrical energy to power the sensing devices[11–13, 23]. With the continuous development of IoT and their pervasive applications [6, 8, 9, 16, 35], many manufacturers has already considered this solution. Specifically, many modern IoT devices are equipped with solar cells [1] in an attempt to enable completely battery-free operation [15]. Motivated by this, we attempt to answer the following question: *is it possible to find a relation between the user location in the environment and the amount of harvested energy?*

In this paper, we study how the amount of harvested energy encodes information about the underlying physical processes and thus, the photovoltaic (solar) cells can be used as a sensor. Additionally, we propose *SoLoc*: a system that uses photocurrent generated by the photovoltaic cells to localize users in the vicinity in a device-free manner. The basic principle is that the location of the bystander interferes with the lighting received by the photovoltaic cells, thus producing a location fingerprint on the generated photocurrents. *SoLoc* employs a probabilistic approach to estimate the user location whose pattern matches the captured photocurrent with maximum likelihood. This approach yields a sub-meter localization accuracy confirming its ability to handle the uncertainty of the measured noisy photocurrents while ensuring low computational requirements.

The rest of the paper is structured as follows. Section 2 motivates the adoption of photovoltaic cells. Section 3 introduces the detailed implementation of the proposed *SoLoc* system. We validate *SoLoc* performance in Section 4. Finally, we conclude the paper in Section 5.

2 MOTIVATION

2.1 Energy Harvesters

Photovoltaic cells are the most commonly used energy harvester to power IoT devices [11, 32]. This is because they are widely available and easily installed in indoor and outdoor environments. Also, they are used in various applications, including handheld calculators, garden lights, and wearable devices [11–13]. Bhatti et. al., [3], showed that visible light offers higher efficiency and robustness compared to other energy harvesters, e.g., kinetic energy. Additionally, when the indoor user interferes with the ambient light, this yields distinct harvesting patterns depending on her location. This observation introduces a unique opportunity to use photovoltaic cells as a sensor for location estimation as well as energy harvesting.

[1]A solar/photovoltaic cell is a semiconductor-based device that generates an electric current (photocurrent) when light falls on its surface.

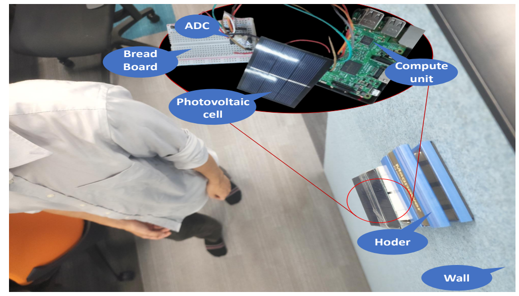

Figure 2: *SoLoc* installed in the environment.

2.2 Photovoltaic cells in the market

The global market for Indoor photovoltaics (IPV) cells was $140 million USD in 2017 [14]. This is achieved due to their coupling to the IoT market. However, recent market studies expect significant growth of the annual IPV market size with more than 850 million and one billion USD by 2023 and 2024, respectively. This will accompany the demand for photovoltaic cells with 60 million devices annually. This market is growing at an unprecedented pace compared to other energy harvesters. Given the dense presence of indoor ambient lighting, IoT manufacturers tend to improve commercialization by equipping modern smart devices with PV cells for energy harvesting. This has set true with the development of a new type of cells that are transparent and thin. This unleashes unique opportunities for context-aware sensing as well as energy harvesting in indoor environments. User location is one of the most valuable context information for a large number of applications.

3 THE *SOLOC* SYSTEM

We present the details of the proposed system. The system consists of two stages: *Sensing Stage* and *Intelligence Stage*.

3.1 The Sensing Stage

3.1.1 The basic idea. The rationale behind *SoLoc*, is using photovoltaic cells as a sensing device for enabling indoor localization based on solar energy harvesting theory. Photovoltaic cells are devices that convert the energy of light into electrical energy through the photovoltaic effect [17]. The amount of generated energy is usually measured by photocurrent, which is a function of several factors, such as intensity, angle, wavelength of the incident light and the cell characteristics (form factor and current density[2]). Current density is a measure of photovoltaic energy harvesting efficiency depending on the wavelength of the incident light, i.e., the light spectrum. Current density increases linearly with the light intensity [4]. Therefore, the light received by a photovoltaic cell may be blocked when the user is in the proximity of the cell, and thus, the generated photocurrent will decrease (Fig. 1). In this vein, when multiple photovoltaic cells are exploited, a specific human location will leave a unique signature on the photocurrent measurements of different cells, thereby enabling accurate human positioning.

3.1.2 Implementation. We used off-the-shelf commercial photovoltaic cell (Fig.2) of 15.5% efficiency with dimensions (length, width and depth) of 10cm, 7cm and 0.15cm. For capturing the photocurrent readings from a photovoltaic cell, we connected the photovoltaic cell to an analog to digital converter (ADC) whose output is fed

[2]the current density is defined as the amount of photocurrent generated per unit area (e.g., mA/cm^2).

to a Raspberry Pi (RPI) module (Fig. 2). The RPI is connected to the environment's LAN via Wi-Fi module. The measurements are recorded using our Python implementation, which sends an HTTP request to the installed RPIs to get the response of photocurrent readings from their connected photovoltaic cells. These readings are aggregated into one sample, which is stored in our fingerprint database.

3.2 The Intelligence Stage

The *SoLoc* system works in two subsequent phases: an offline fingerprinting phase and an online tracking phase. During **the offline phase**, the system tabulates the recorded photocurrent from the photovoltaic cells at predefined reference locations in the area of interest, resulting in a so-called photovoltaic map. In **the tracking phase**, the system uses the captured photocurrent received from the photovoltaic cells to find the reference locations whose pattern is the most similar. Then, *SoLoc* processes these locations to obtain a more accurate location of the user in the continuous space.

3.2.1 Offline phase. During the offline phase, *SoLoc* constructs the histogram of the photocurrent measurements of each photovoltaic cell at each user location. These histograms represent the *SoLoc* system's photovoltaic map. The photocurrent histogram can be approximated by a parametric distribution such as the Gaussian distribution. More formally, assume L to be a $2D$ space. At each location $l \in L$, we can get a photocurrent vector from k photovoltaic cells. We denote the k-dimensional photocurrent space as S. Each element in this space is a k-dimensional vector whose entries represent the photocurrent readings from different photovoltaic cells. We denote samples from the photocurrent space S as s. We also assume that the samples from different photovoltaic cells are independent. The problem becomes, given a photocurrent vector $s = (s_1, ..., s_k)$, we want to find the location $l \in L$ that maximizes the probability $P(l/s)$.

3.2.2 Online Tracking phase. This phase aims to locate the user in real-time, after deploying the system, using the measured photocurrent from the installed photovoltaic cells. Specifically, the user is at an unknown location while each photovoltaic cell produces a photocurrent corresponding to the received light density in the area of interest. Then, the measured photocurrent values are used to estimate the user location with the maximum probability. Given a photocurrent vector $s = (s_1, ..., s_k)$, we want to find the reference location $l^* \in L$ that maximizes the probability $P(l \mid s)$. This can be formalized using Bayes' theorem as:

$$l^* = \underset{l}{\operatorname{argmax}}[P(l \mid s)] = \underset{l}{\operatorname{argmax}}\left[\frac{P(s \mid l)P(l)}{P(s)}\right] \tag{1}$$

Assuming all the reference points have equal probability:

$$\underset{l}{\operatorname{argmax}}[P(l \mid s)] = \underset{l}{\operatorname{argmax}}[P(s \mid l)] \tag{2}$$

$P(s \mid l)$ can be calculated using the Gaussian densities of photocurrent constructed in the offline phase as:

$$P(s \mid l) = \prod_{i=1}^{k} P(s_i \mid l) \tag{3}$$

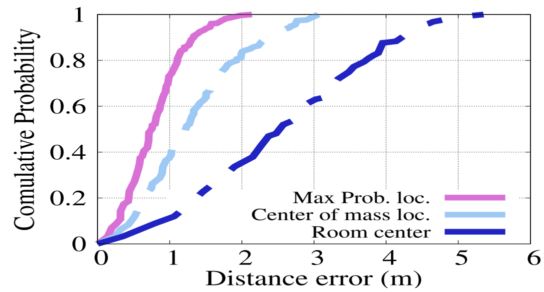

Figure 3: CDF of the localization error.

A representative location for the most probable reference location (l^*) can be reported as the estimated location. However, estimating the user location as one of the reference discrete locations leads to poor user experience, especially when the reference locations are spaced-out. Thus, to track the user in the continuous space, *SoLoc* reports the center of mass of all reference locations weighted by their corresponding probabilities, as:

$$(l_x, l_y) = \left(\frac{\sum_{i=1}^{n} P_i l_{ix}}{\sum_{i=1}^{n} P_i}, \frac{\sum_{i=1}^{n} P_i l_{iy}}{\sum_{i=1}^{n} P_i}\right) \tag{4}$$

where l_{ix} and l_{iy} are the spatial coordinates of i^{th} reference location, and P_i is its corresponding probability.

4 EVALUATION

4.1 Environmental Setup

The environment of interest, is equipped with several photovoltaic cells distributed uniformly on walls. The room is illuminated with a chandelier of 8 lamps of 40 watt each, i.e., 450 lumens. This light source is hanged in the center of the room's ceiling at height 1.9m from the floor. The experimental area is partitioned into a uniform virtual grid (i.e., cells have equal sizes). Then, the photocurrent measurements corresponding to the received light are recorded while the user is located at an arbitrary grid cell in the environment. The data is collected while the user stands at the center of each grid cell (i.e., reference points). We collected 50 samples of photocurrent readings at 24 locations.

4.2 Performance Evaluation

Fig. 3 shows the cumulative distribution function of the Euclidean distance error of *SoLoc*. The figure shows that *SoLoc* achieves 0.8m and 1.2 median accuracy using the center of mass and the maximum probable location methods, respectively. This confirms the efficacy of smoothing the output location in the continuous space, which yields fine-grained estimates. This is better than the strawman approach that always calculates the user location at the center of the room. Considering that the sensing has been done only with harvested energy, we believe this result paves the road for the next generation of battery-less context-aware sensing systems.

5 CONCLUSION

We presented *SoLoc*, an accurate and reliable device-free energy-free indoor localization system that uses photocurrent measurements of photovoltaic cells to localize users without wearing or carrying any device. We showed how *SoLoc* defines a photocurrent signature for each location in the environment. These signatures are further used to build a probabilistic fingerprint database that enable fine-grained estimation of the user location using probabilistic model. We evaluated *SoLoc* in a realistic environment on a regular working day.

ACKNOWLEDGMENT

This work was partially funded by the Australian Research Council Discovery Project DP210100904 and the Grant-in-Aid for Scientific Research (C) (Grant number 22K12011) from the Japan Society for the Promotion of Science (JSPS).

The authors would like to thanks Rola Elbakly for her assistance in the data collection process.

REFERENCES

[1] Moustafa Abbas, Moustafa Elhamshary, Hamada Rizk, Marwan Torki, and Moustafa Youssef. 2019. WiDeep: WiFi-based Accurate and Robust Indoor Localization System using Deep Learning. In *Proceedings of the International Conference on Pervasive Computing and Communications (PerCom)*. IEEE.

[2] Khaled Alkiek, Aya Othman, Hamada Rizk, and Moustafa Youssef. 2020. Deep Learning-based Floor Prediction Using Cell Network Information. In *Proceedings of the 28th International Conference on Advances in Geographic Information Systems*. 663–664.

[3] Naveed Anwar Bhatti, Muhammad Hamad Alizai, Affan A. Syed, and Luca Mottola. 2016. Energy Harvesting and Wireless Transfer in Sensor Network Applications: Concepts and Experiences. *ACM Trans. Sen. Netw.* 12, 3, Article 24 (aug 2016), 40 pages. https://doi.org/10.1145/2915918

[4] Xiaomei Cai, Shengwei Zeng, Xin Li, Jiangyong Zhang, Shuo Lin, Ankai Lin, and Baoping Zhang. 2011. Effect of light intensity and temperature on the performance of GaN-based pin solar cells. In *Electrical and Control Engineering (ICECE), 2011 International Conference on*. IEEE, 1535–1537.

[5] Pavel Davidson and Robert Piché. 2017. A survey of selected indoor positioning methods for smartphones. *IEEE Communications Surveys & Tutorials* 19, 2 (2017), 1347–1370.

[6] Viktor Erdélyi, Hamada Rizk, Hirozumi Yamaguchi, and Teruo Higashino. 2021. Learn to See: A Microwave-Based Object Recognition System Using Learning Techniques. In *Adjunct Proceedings of the 2021 International Conference on Distributed Computing and Networking (ICDCN '21)*. Association for Computing Machinery, New York, NY, USA, 145–150. https://doi.org/10.1145/3427477.3429459

[7] Israa Fahmy, Samah Ayman, Hamada Rizk, and Moustafa Youssef. 2021. MonoFi: Efficient Indoor Localization Based on Single Radio Source And Minimal Fingerprinting *(SIGSPATIAL '21)*. Association for Computing Machinery, New York, NY, USA, 674–675. https://doi.org/10.1145/3474717.3486808

[8] Hikaru Katayama, Teruhiro Mizomoto, Hamada Rizk, and Hirozumi Yamaguchi. 2022. You Work We Care: Sitting Posture Assessment Based on Point Cloud Data. In *PerCom Workshops*. 121–123. https://doi.org/10.1109/PerComWorkshops53856.2022.9767292

[9] Betty Lala, Hamada Rizk, Srikant Manas Kala, and Aya Hagishima. 2022. Multi-Task Learning for Concurrent Prediction of Thermal Comfort, Sensation and Preference in Winters. *Buildings* 12, 6 (2022). https://doi.org/10.3390/buildings12060750

[10] Liqun Li, Pan Hu, Chunyi Peng, Guobin Shen, and Feng Zhao. 2014. Epsilon: A visible light based positioning system. In *11th {USENIX} Symposium on Networked Systems Design and Implementation ({NSDI} 14)*. 331–343.

[11] Dong Ma, Guohao Lan, Mahbub Hassan, Wen Hu, and Sajal K Das. 2019. Sensing, computing, and communications for energy harvesting IoTs: A survey. *IEEE Communications Surveys & Tutorials* 22, 2 (2019), 1222–1250.

[12] Dong Ma, Guohao Lan, Mahbub Hassan, Wen Hu, Mushfika Baishakhi Upama, Ashraf Uddin, and Moustafa Youssef. 2018. Gesture recognition with transparent solar cells: A feasibility study. In *the 12th International Workshop on Wireless Network Testbeds, Experimental Evaluation & Characterization*. ACM, 79–88.

[13] Dong Ma, Guohao Lan, Mahbub Hassan, Wen Hu, Mushfika B Upama, Ashraf Uddin, and Moustafa Youssef. 2019. SolarGest: Ubiquitous and battery-free gesture recognition using solar cells. In *The 25th Annual International Conference on Mobile Computing and Networking*. ACM, 1–15.

[14] Ian Mathews, Sai Nithin Kantareddy, Tonio Buonassisi, and Ian Marius Peters. 2019. Technology and Market Perspective for Indoor Photovoltaic Cells. *Joule* 3, 6 (2019), 1415–1426. https://doi.org/10.1016/j.joule.2019.03.026

[15] Ian Mathews, Sai Nithin Kantareddy, Tonio Buonassisi, and Ian Marius Peters. 2019. Technology and market perspective for indoor photovoltaic cells. *Joule* 3, 6 (2019), 1415–1426.

[16] Yuma Okochi, Hamada Rizk, and Hirozumi Yamaguchi. 2022. On-the-Fly Spatio-Temporal Human Segmentation of 3D Point Cloud Data By Micro-Size LiDAR. In *Proceedings of The 18th International Conference on Intelligent Environments (IE2022). IEEE.*

[17] Bhubaneswari Parida, S_ Iniyan, and Ranko Goic. 2011. A review of solar photovoltaic technologies. *Renewable and sustainable energy reviews* 15, 3 (2011), 1625–1636.

[18] Hamada Rizk. 2019. Device-Invariant Cellular-Based Indoor Localization System Using Deep Learning. In *The ACM MobiSys 2019 on Rising Stars Forum (RisingStarsForum'19)*. ACM, 19–23.

[19] Hamada Rizk. 2019. Solocell: Efficient indoor localization based on limited cell network information and minimal fingerprinting. In *Proceedings of the 27th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems*. 604–605.

[20] Hamada Rizk, Moustafa Abbas, and Moustafa Youssef. 2020. OmniCells: Cross-Device Cellular-based Indoor Location Tracking Using Deep Neural Networks. In *the International Conference on Pervasive Computing and Communications (PerCom)*. IEEE.

[21] Hamada Rizk, Moustafa Abbas, and Moustafa Youssef. 2021. Device-independent cellular-based indoor location tracking using deep learning. *Pervasive and Mobile Computing* (2021), 101420.

[22] Hamada Rizk, Ahmed Elmogy, and Hirozumi Yamaguchi. 2022. A Robust and Accurate Indoor Localization Using Learning-Based Fusion of Wi-Fi RTT and RSSI. *Sensors* 22, 7 (2022). https://doi.org/10.3390/s22072700

[23] Hamada Rizk, Dong Ma, Mahbub Hassan, and Moustafa Youssef. 2022. Indoor Localization using Solar Cells. In *2022 IEEE International Conference on Pervasive Computing and Communications Workshops and other Affiliated Events (PerCom Workshops)*. 38–41. https://doi.org/10.1109/PerComWorkshops53856.2022.9767256

[24] Hamada Rizk, Asmaa Saeed, and Hirozumi Yamaguchi. 2022. Vaccinated, What Next? An Efficient Contact and Social Distance Tracing Based on Heterogeneous Telco Data. *IEEE Sensors Journal* (2022), 1–1.

[25] Hamada Rizk, Ahmed Shokry, and Moustafa Youssef. 2019. Effectiveness of Data Augmentation in Cellular-based Localization Using Deep Learning. In *Proceedings of the International Conference on Wireless Communications and Networking Conference (WCNC)*. IEEE.

[26] Hamada Rizk, Marwan Torki, and Moustafa Youssef. 2018. CellinDeep: Robust and Accurate Cellular-based Indoor Localization via Deep Learning. *IEEE Sensors Journal* (2018).

[27] Hamada Rizk, Hirozumi Yamaguchi, Teruo Higashino, and Moustafa Youssef. 2020. A Ubiquitous and Accurate Floor Estimation System Using Deep Representational Learning. In *Proceedings of the 28th International Conference on Advances in Geographic Information Systems*. 540–549.

[28] Hamada Rizk, Hirozumi Yamaguchi, Moustafa Youssef, and Teruo Higashino. 2020. Gain without pain: Enabling fingerprinting-based indoor localization using tracking scanners. In *The 28th International Conference on Advances in Geographic Information Systems*. 550–559.

[29] Hamada Rizk, Hirozumi Yamaguchi, Moustafa Youssef, and Teruo Higashino. 2022. Laser Range Scanners for Enabling Zero-Overhead WiFi-Based Indoor Localization System. *ACM Transaction on Spatial Algorithms Systems* (may 2022).

[30] Hamada Rizk and Moustafa Youssef. 2019. MonoDCell: A Ubiquitous and Low-Overhead Deep Learning-based Indoor Localization with Limited Cellular Information. In *the 27th ACM SIGSPATIAL International Conference*. ACM, 109–118.

[31] Asmaa Saeed, Ahmed Wasfey, Hamada Rizk, and Hirozumi Yamaguchi. 2022. CellStory: Extendable Cellular Signals-Based Floor Estimator Using Deep Learning. In *2022 18th International Conference on Intelligent Environments (IE)*. 1–4. https://doi.org/10.1109/IE54923.2022.9826773

[32] Muhammad Moid Sandhu, Sara Khalifa, Kai Geissdoerfer, Raja Jurdak, and Marius Portmann. 2021. SolAR: Energy positive human activity recognition using solar cells. In *2021 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. IEEE, 1–10.

[33] Ahmed Shokry and Moustafa Youssef. 2022. A Quantum Algorithm for RF-based Fingerprinting Localization Systems. In *2022 IEEE 47th Conference on Local Computer Networks (LCN)*. 18–25. https://doi.org/10.1109/LCN53696.2022.9843246

[34] Xuyu Wang, Lingjun Gao, Shiwen Mao, and Santosh Pandey. 2015. DeepFi: Deep learning for indoor fingerprinting using channel state information. In *Proceedings of the International Conference on Wireless Communications and Networking*. IEEE, 1666–1671.

[35] Shota Yamada, Hamada Rizk, and Hirozumi Yamaguchi. 2022. An Accurate Point Cloud-Based Human Identification Using Micro-Size LiDAR. In *PerCom Workshops*. 569–574.

[36] Moustafa Youssef and Mahbub Hassan. 2019. Next Generation IoT: Toward Ubiquitous Autonomous Cost-Efficient IoT Devices. *IEEE Pervasive Computing* 18, 4 (2019), 8–11. https://doi.org/10.1109/MPRV.2019.2947974

[37] Chi Zhang and Xinyu Zhang. 2016. LiTell: robust indoor localization using unmodified light fixtures. In *Proceedings of the 22nd Annual International Conference on Mobile Computing and Networking*. ACM, 230–242.