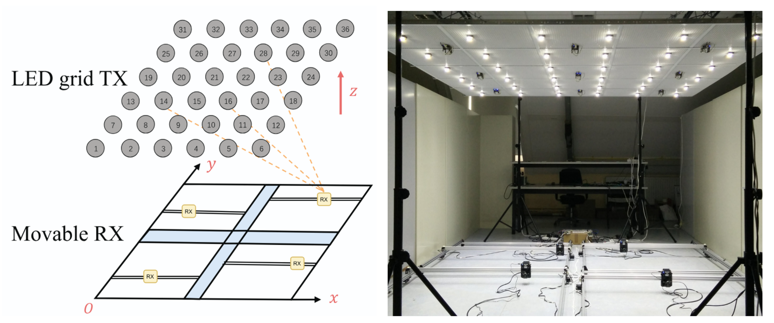
TinyML-Empowered Indoor Positioning with Light: A Study on the Impact of LED Aging and Failure

Joey Wenyi Li [1] Ran Zhu [1] Qing Wang [1]

[1]Delft University of Technology

1. Introduction



(a) Schematic (b) Testbed

Figure 1. DenseVLC system setup [1]

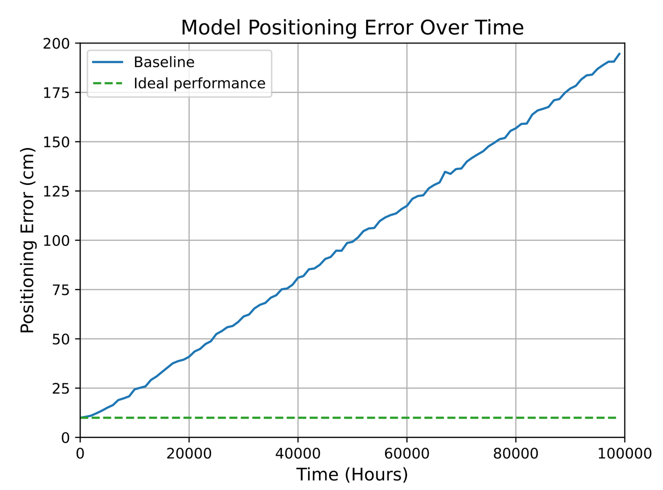


Figure 2. Impact of degradation on positioning accuracy

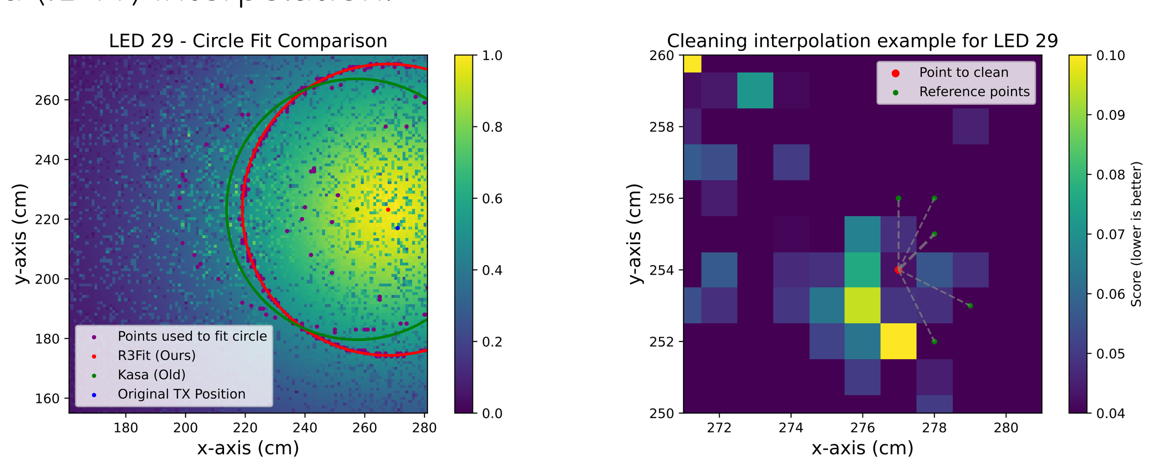
Visible Light Positioning (VLP) uses LED lights to determine the position of objects or people indoors, offering an accurate and cost-effective alternative to traditional positioning systems like GPS [4]. However, its accuracy degrades significantly when the LEDs themselves degrade.

As a basis for this research, we take the VLP system designed by Zhu et al. [3] as our baseline.

Research Question How can we efficiently pre-process data for visible light positioning to reduce fingerprinting needs, maintain accuracy, and ensure resilience to infrastructure degradation?

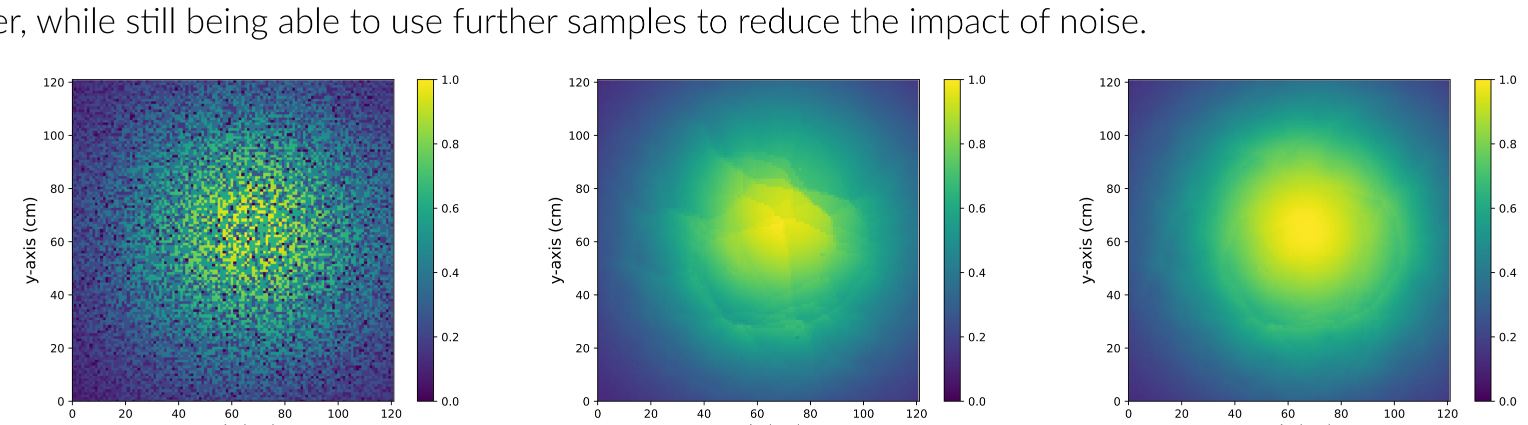
2. Improving LED Cleaning

To improve data cleaning, we propose using more accurate LED positions, as well as using inverse distance weighted (IDW) interpolation.



(a) Position estimation on raw data for LED 18. (b) Data cleaning with IDW, colors show the sample quality score.

Figure 3. Our changes made to the data cleaning methods. The LED position is able to be estimated much more accurately without any preprocessing having to be done. The interpolation correctly weighs closer samples much heavier, while still being able to use further samples to reduce the impact of noise.

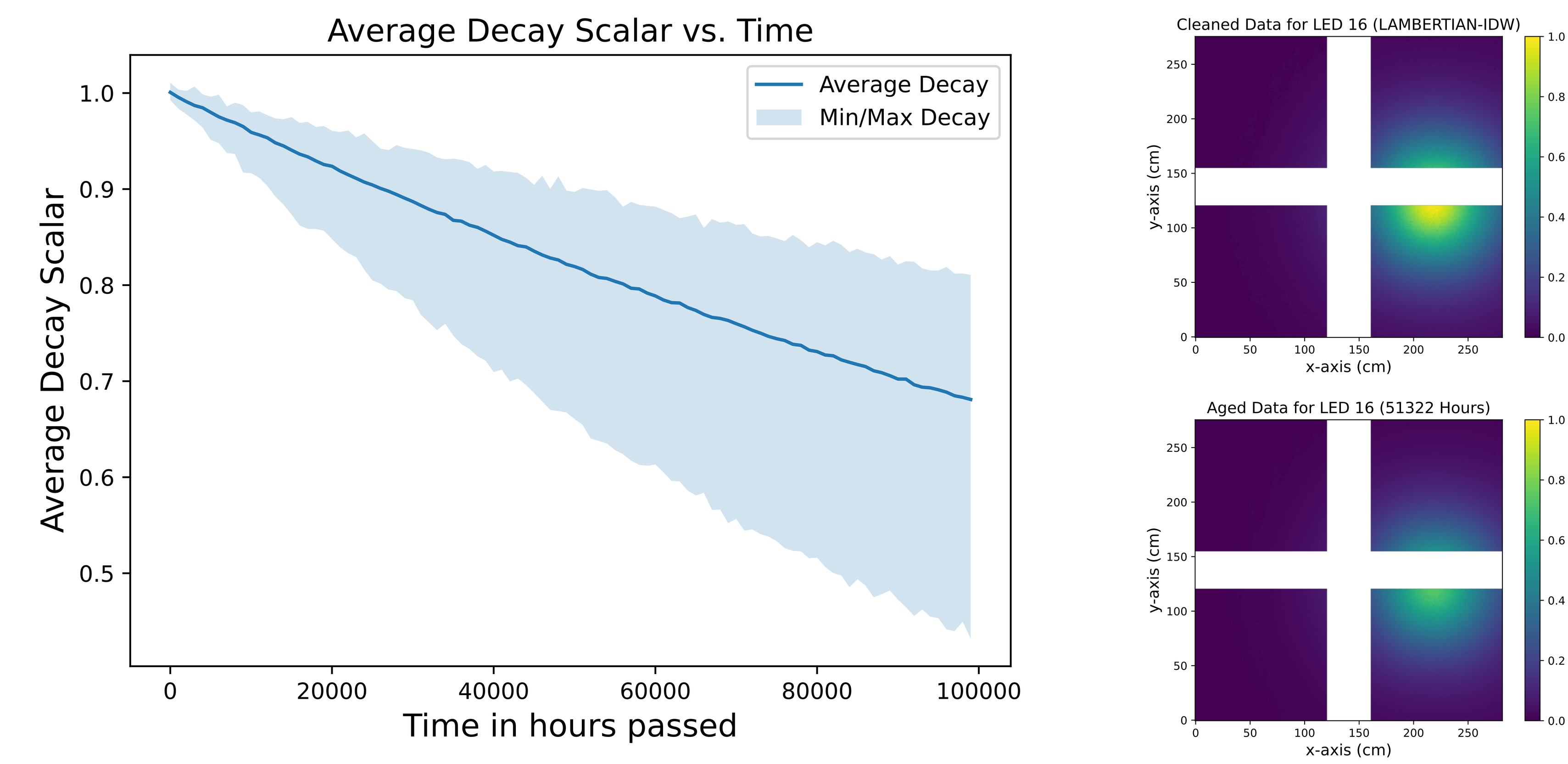


(a) Raw LED 7 (b) Old clean LED 7 (c) Improved clean LED 7

Figure 4. Cleaning results for LED 7: (a) No cleaning, (b) old cleaning method, and (c) improved cleaning using Inverse Distance Weighting (IDW) and more accurate LED positions. The improved method shows higher reliability in reconstructing missing or noisy data points, especially under low signal-to-noise conditions.

3. LED Degradation Modeling

To assess how LED degradation affects our solution, we developed a simulation framework to model the effects of LED aging and failure on the visible light positioning system based on the TM-21 model [2].



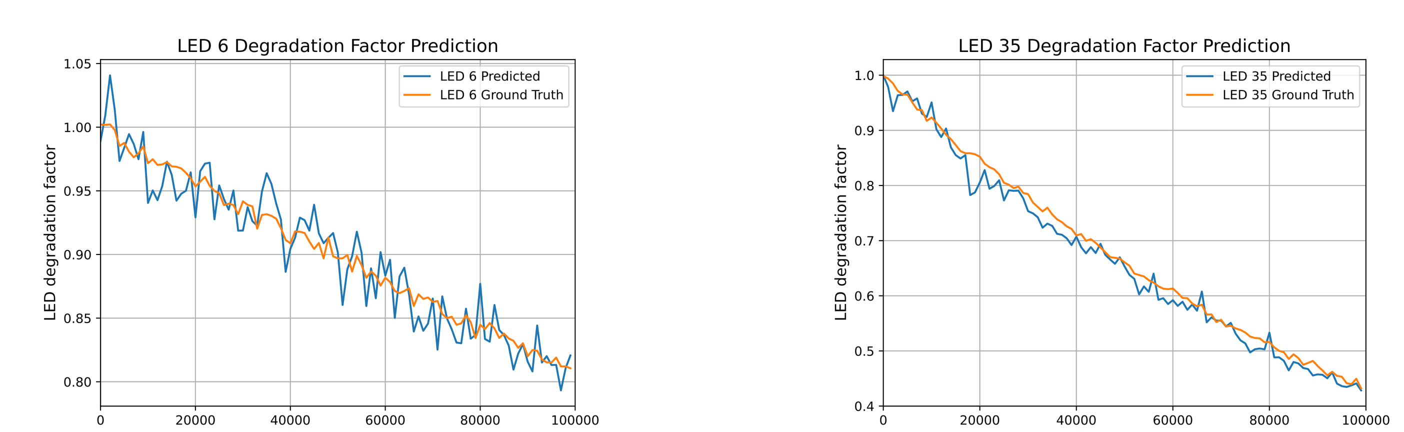
(a) Decay over time for all LEDs. Notice how all LEDs have drastically different decay patterns. This is the most pessimistic case, making it perfect to benchmark against.

(b) New vs aged data.

Figure 5. Figures showing LED degradation and signal comparison. The left subfigure presents the decay in light output over time for multiple LEDs. The right subfigures compare signal data from a new LED and one that has decayed.

4. Compensating LED Degradation with Processing and Online Learning

Our method combines data augmentation with online learning in order to combat LED degradation. By keeping a pool of samples and comparing these to their predicted reference using a RANSAC-based method, we are able to accurately predict the degradation factor of the LED.



(a) Degradation prediction for a relatively robust LED. (b) Degradation prediction for a relatively short-lived LED.

Figure 6. Degradation scalar prediction for 2 LEDs predicted in the same simulation run. Note how regardless of the trend, our prediction model is able to correctly predict and thus mitigate degradation.

5. Results

We compare positioning accuracy across different processing methods under varying LED degradation levels. This demonstrates our method's robustness to LED aging, without requiring any re-fingerprinting.

Table 1. Different model accuracy over time when effected by LED degradation.

Model	t=0	t=25000	t=50000	t=75000	t=100000
Baseline (Zhu *et al.*) [3]	9.97	48.78	98.60	145.16	194.53
Residual MLP (Ours)	7.43 (-26%)	16.88 (-65%)	32.72 (-67%)	47.78 (-67%)	64.22 (-67%)
Baseline + Online Learning	11.71 (+17.5%)	13.23 (-73%)	14.66 (-85%)	12.99 (-91%)	14.87 (-92%)
Residual MLP + Online Learning	**8.45** (-15%)	**10.59** (-78%)	**9.96** (-90%)	**9.10** (-94%)	**8.12** (-96%)

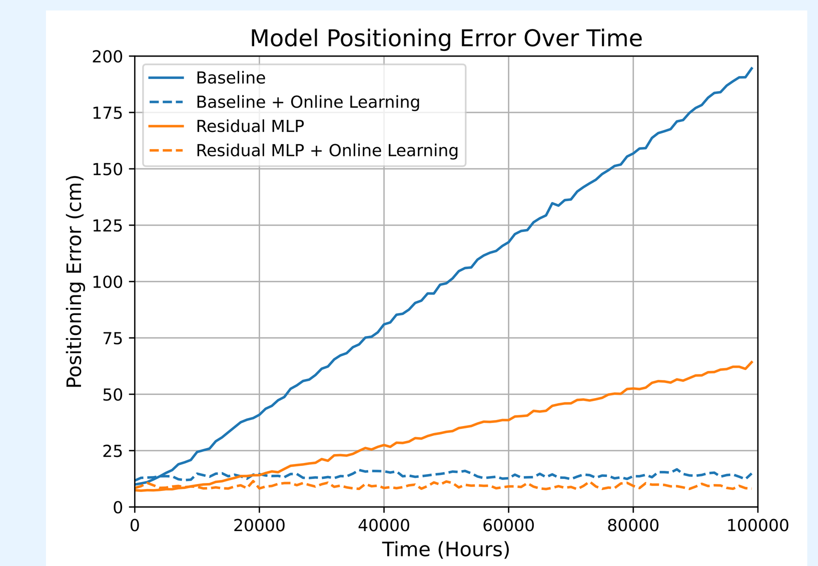


Figure 7. Positioning error over time for the baseline and the proposed model, each evaluated with and without online learning. In both cases, the error remains stable over time when our online learning method is applied.

6. Conclusions

We address two key challenges in Visible Light Positioning (VLP): LED degradation and the cost of dense fingerprinting. Our contributions include:

- Improved data cleaning via early LED positions and IDW.
- A simulation framework for LED aging and failure, including flickering and random noise.
- Online learning with RANSAC-based degradation correction.

Our method reduces positioning error by up to **96%** under heavy degradation, with no need for re-fingerprinting. This demonstrates the potential of TinyML and lightweight adaptation for robust, low-maintenance indoor localization.

References

[1] Jona Beysens, Ander Galisteo, Qing Wang, Diego Juara, Domenico Giustiniano, and Sofie Pollin. Densevlc: a cell-free massive mimo system with distributed leds. In *Proceedings of the 14th International Conference on Emerging Networking EXperiments and Technologies*, CoNEXT '18, page 320–332, New York, NY, USA, 2018. Association for Computing Machinery.

[2] TM-21 Working Group et al. Projecting long term lumen maintenance of led light sources (ies tm-21-11). *New York, NY, USA: Illuminating Engineering Society of North America (IESNA)*, 2008.

[3] Ran Zhu, Maxim Van den Abeele, Jona Beysens, Jie Yang, and Qing Wang. Centimeter-level indoor visible light positioning. *IEEE Communications Magazine*, 62(3):48–53, 2024.

[4] Zhiyu Zhu, Yang Yang, Mingzhe Chen, Caili Guo, Julian Cheng, and Shuguang Cui. A survey on indoor visible light positioning systems: Fundamentals, applications, and challenges. *IEEE Communications Surveys and Tutorials*, pages 1–1, 2024.