When BLE Meets Light: Multi-modal Fusion for Enhanced Indoor Localization

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ABSTRACT

Designing a reliable and highly accurate indoor localization system is challenging due to the non-uniformity of indoor spaces, multipath fading, and satellite signal blockage. To address these issues, we propose a Deep Neural Network-based localization system that combines *passive* Visible Light Positioning (*p*-VLP) and Bluetooth Low Energy (BLE) technologies to achieve stable, energy-efficient, and accurate indoor localization. Our solution leverages incremental learning to fuse data from visible light and BLE, overcoming their individual limitations and achieving centimeter-level localization accuracy. We build a prototype using low-cost S9706 hue sensors for *p*-VLP and low-power nrf52830 BLE boards to collect data simultaneously from both technologies in a $25m^2$ testbed. Our approach demonstrates a significant localization accuracy improvement of approximately 47% and 64% compared to individual *p*-VLP and BLE technologies, respectively, achieving a mean localization error of 20 cm.

CCS CONCEPTS

• **Networks** → *Location based services*; • **Computing methodologies** → *Neural networks*.

KEYWORDS

Multi-modal fusion, visible light positioning, Bluetooth 5.1

1 INTRODUCTION

Building smart indoor environments has intensified the need to design more accurate indoor localization systems.

Difficult Commercialization & Limited Usable Range. One promising technology for highly-accurate indoor localization is Visible Light Positioning (VLP), which utilizes light's directive properties for precise indoor localization. However, existing VLP systems perform well only in controlled environments. In real-world scenarios, factors like external ambient light sources, obstacles, and shadows, decline localization performance, ultimately restricting the e ective localization areas. Additionally, active VLP systems have limited market adoption due to luminaire design changes [5].

Limited Accuracy. In contrast, RF technologies like Bluetooth Low Energy (BLE) have gained popularity for indoor localization due to their ubiquity and low-cost hardware. However, BLE's narrowband nature makes it susceptible to multipath fading, limiting ranging accuracy. The angle of arrival/departure techniques can utilize signal phase information to overcome this. However, they require multiple antennas, typically sized 16×16 cm, which are bulky, expensive, and challenging to acquire commercially [3].

Hybrid Localization? To address these challenges, this paper investigates combining BLE and VLP to design a reliable, accurate hybrid localization system. We aim to overcome BLE's low accuracy and VLP's limited usage range by leveraging both technologies' strengths. Our system utilizes unmodulated light sources' inherent characteristics, specifically the power at dominant wavelengths, via single-pixel hue sensors, without modifying existing lighting infrastructure. Additionally, we leverage BLE 5.1 standard and employ Constant Tone Extension (CTE), a waveform with constant frequency and amplitude [1, 3], to collect Received Signal Strength (RSS) using a single antenna. Furthermore, we leverage Deep Neural Networks (DNNs) to e ectively fuse signal features from both technologies. DNNs show promise in modeling the mapping between signal features and target locations, addressing multipath complexity in indoor areas [3]. Our **contributions** are summarized as follows:

i) We propose BLELight, a hybrid accurate localization system for large indoor spaces. BLELight fuses the intrinsic features of unmodulated light (the ratio of power at dominant wavelengths) with the BLE signal strength.
ii) We propose an incremental learning-based approach to train the DNN model, leveraging the multimodality features for the purpose of localization.
iii) We build a testbed using a single-pixel hue sensors for *p*-VLP and nrf528350 BLE board on a mobile target. We collect real-time data to experimentally validate BLELight.
iv) Our preliminary experimental results demonstrate that BLELight achieves a mean localization error of ~20cm, improving the localization performance of individual *p*-VLP and BLE by about 47% and 64%, respectively.

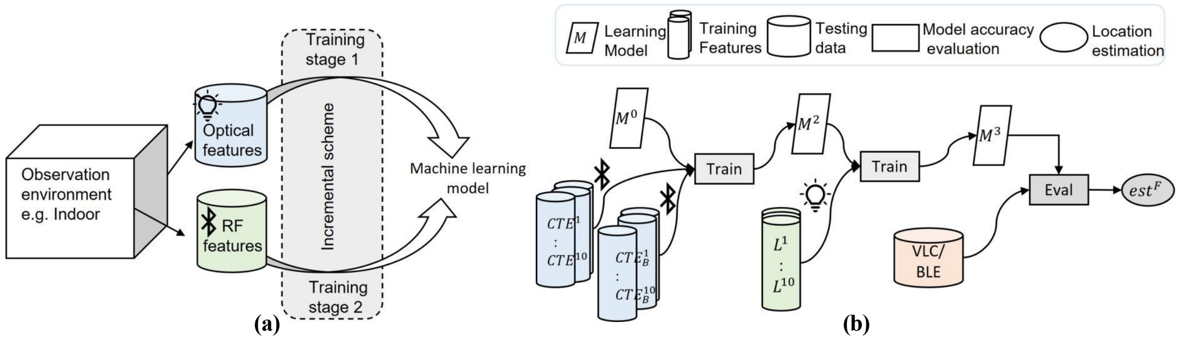


Figure 1: The proposed BLELight: (a) multi-modality model; (b) incremental learning scheme in which BLE and *passive*-VLP features are fed into the DNN model at different training stages to improve the localization performance.

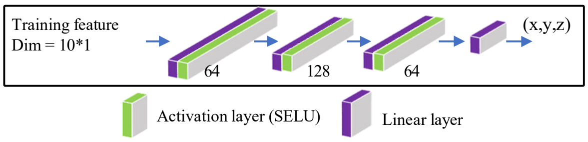


Figure 2: The designed DNN architecture in BLELight.

2 PRELIMINARIES

To avoid modifying the lighting infrastructure for transmitting location beacons, our BLELight leverages the intrinsic hue characteristics of the lights to establish a distinct light signature. Specifically, we utilize the power ratios at dominant wavelengths ($\lambda_Æ$ (red), λ_G (green), and λ_B (blue)) of white light sources. We define the unique light signature as $< P_B/P_G, P_G\,/P_Æ, P_B/P_Æ >$, detailed in [6]. While the light signature of a particular light source should remain consistent within its illuminated area, the presence of other light sources and amb ient light may introduce interference. However, it is found that this added interference is not significant (often below 10% [6]), and does not provide substantial information to perform localization. This is due to the inherent intrinsic nature of the extracted light signature. Nevertheless, a Machine Learning (ML) model can learn these slight variations over distance, o ering localization capabilities. This aspect serves as one of the motivations for BLELight.

Furthermore, low light conditions or blocking of light sensors can disrupt the localization. To address this, we combine light measurements with BLE RSS measurements, especially utilizing BLE 5.1's CTE feature. Moreover, to enhance the e ectiveness of the DNN model, we incorporate the BLE RSS measurements found in the beating spectrum (details provide in [4]). This provides us with pairwise contributions of the power amplitude of anchor nodes at target locations. For instance, let's consider four BLE anchor nodes tuned at frequencies f_1, f_2, f_3, and f_4. At the mobile tag, we extract power amplitudes at these frequencies from both the signal frequency spectrum and the beating spectrum [4]. The beating spectrum analysis yields power amplitudes at frequencies $(f_1 - f_2, f_2 - f_3, f_1 - f_3, f_1 - f_4, f_2 - f_4, f_3 - f_4)$. This fine-grained RSS analyzed from beating spectrum significantly improves the localization accuracy as shown in [4], and it enhances the learning capability of our ML model in BLELight.

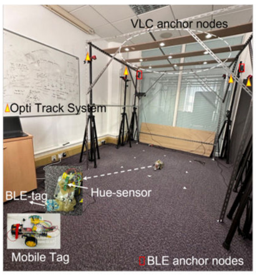
3 BLELIGHT: MULTI-MODAL FUSION

Framework: BLELight focuses on the indoor environment with multi-modality observations (see Figure 1a). Specifically, we fuse the modalities p-VLP and BLE, training a DNN model using an Incremental Learning (IL) approach. IL is a learning paradigm that allows models to continuously adapt and update their knowledge when new data becomes available. Despite the di erences in BLE and p-VLP modalities, they both reflect the signal-location relationship or distribution within a specific indoor environment. Therefore, leveraging these two signal features jointly can enhance localization accuracy. Moreover, IL o ers the advantage of reducing feature interference or imbalance from di erent sources. By training the DNN model with one signal feature at a time during each stage, we can mitigate the interference caused by multiple sources and ensure a more focused learning process.

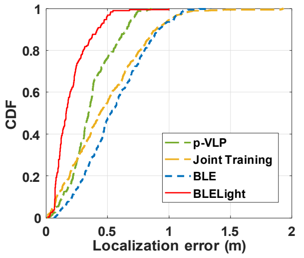
Sytsem Design: Figure 1b illustrates the architecture of BLELight using an IL-based technique. In the training phase, the first step incorporates features from BLE, specifically those extracted from both signal and beating spectrums [4]. IL allows the DNN model to gradually improve its comprehension of location-related features. In the second stage, the trained model continues to enhance its localization capabilities by leveraging the light signature features. The evaluation of localization performance can be conducted at each stage. The DNN model adopted in BLELight is a fully connected NN, whose architecture is shown in Figure 2. The input is a 10×1 vector, and the output is the estimated location coordinates (x, y, z). SELU is adopted as the activation function in the layers between input and output.

4 TESTBED & DATA COLLECTION

Testbed: A LED network is built with 9 o -the-shelf white LEDs, covering a $10m^2$ area. LEDs are positioned with an inter-distance of ~55cm from the center of each LED to induce interference (field of view of 36°). Besides, we utilize four BLE anchors arranged in a square within a $25m^2$ area.



(a) Testbed



(b) p-VLP and BLE vs. BLELight

Figure 3: Evaluation: (a) BLELight experimental setup; (b) BLELight localization performance.

Please refer to Figure 3a for visualization. Light sensors and a BLE tag are mounted on a mobile target, enabling simultaneous data collection from both technologies. The testbed, located near windows, allows ambient noise interference for VLP, while its metallic materials create multipath for BLE.

Features selection: Three light hue sensors (S9706 [6]), denoted as $i = 1, 2, 3$, collect light features including power at dominant wavelengths, resulting in light signatures: $< P_{B_i}/P_{G_i}, P_{G_i}/P_{Æ_i}, P_{B_i}/P_{Æ_i}, P_{G_1} - P_{Æ_1} >$. Thus, 10 light features are obtained per target location. For BLE, RSS measurements are taken using nrf52830 (please refer [2] for details), and for each collected packet, we extract 10 features. These features include received power at signal tones (f_1, f_2, f_3, f_4) & beating frequencies ($f_1 - f_2, f_2 - f_3, f_1 - f_3, f_1 - f_4, f_2 - f_4, f_3 - f_4$).

Data Collection: To test the performance of each technology individually, we collect data separately. We collect the p-VLP data all over the area considering the locations directly under the LEDs with no ambient light source, low-light conditions (near the walls) and blocking of the sensor (due to human or testbed metals). Further, for BLELight, we collect the data over di erent days, as the level of ambient light noise is di erent depending on weather conditions. A total of 5 datasets are collected with di erent target heights, comprising 8813 samples for the BLE and 4776 samples for the VLP. We adopt an 80%-20% data split, allocating 80% for training and the remaining 20% for testing.

5 PRELIMINARY RESULTS

We statistically evaluate BLELight using the Communicative Distribution Function (CDF) of localization error, as shown in Figure 3b. We compare the e ectiveness of BLELight with joint training, a widely employed technique for data fusion, wherein all features are simultaneously inputted into a model during a single stage. However, we observe limitations in feature learning and performance improvement with joint training, while BLELight demonstrates clear benefits (see Figure 3b). As IL-enabled continual learning adapts over time, it significantly improves accuracy. By incorporating new information and fine-tuning the model incrementally, we achieve a Mean Localization Error (MLE) of $0.20m$, outperforming the joint training method by up to 58%. Furthermore,

Table 1: 3D Localization error (unit: meter).

	p-VLP	BLE	Joint Learning	Our BLELight
Mean localization error	0.369	0.556	0.48	0.20
Median error	0.34	0.52	0.43	0.16
80th-percentile error	0.54	0.80	0.75	0.29

IL eliminates the general requirements of joint fusion-based approaches, such as maintaining an equal number of samples or features over time. Equalizing sample numbers is challenging due to time synchronization from distinct crystal oscillators and varying sampling rates between the technologies. For simplicity in our comparison, we use equal features for joint training. Additionally, we train separate DNN models for BLE and p-VLP and evaluate their respective performances. Unsurprisingly, BLELight outperforms BLE and p-VLP by about 64% and 47%, respectively. However, it is worth noting that the MLE achieved for BLE is $0.556m$, a notable improvement over classical BLE methods [1], albeit not matching the performance of p-VLP. For comprehensive results, please refer to Table 1. In the future, we will diversify environments and perform cross-validation & ablation studies to assess BLELight's robustness and generalization.

6 CONCLUSION

We explored enhancing indoor localization & overcoming the limitations of BLE and VLP technologies through a hybrid localization system. To maximize the benefits of multimodality features from both technologies, we proposed an incremental learning-based approach to train a DNN. Through experimental evaluation, we verified the e ectiveness of our method, achieving a mean localization error of $20cm$.

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