

# Design of a Device-Robust Bluetooth RSS-Based Localization Framework with Multi-Channel Representation Learning in IoT Environments

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## IoT 환경에서 다중 채널 Bluetooth RSS 표현 학습을 활용한 단말기 이질성 대응 위치 추정 시스템 설계 및 성능 분석

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**Abstract** This study proposes a Bluetooth RSS-based localization framework with multi-channel representation learning to address device heterogeneity in IoT environments. Unlike conventional fingerprint-based approaches, the proposed method directly processes variable-length MAC sets and models RSS using multi-channel features to capture structural signal characteristics. Experiments on the publicly available OutFin dataset show that the proposed model achieves 100% Top-1 and Top-5 accuracy in the in-device setting, outperforming k-NN, SVM, and MLP baselines. Under cross-device evaluation, traditional methods exhibit performance drops of up to 79%, whereas the proposed model maintains 93.74% Top-1 accuracy with only a 6.26% reduction. These results demonstrate that the proposed framework effectively mitigates cross-device degradation and provides robust, generalizable localization in practical IoT environments.

**Key Words** : Bluetooth RSS Localization, Deep Learning-Based Localization, Device Robustness, IoT Positioning System, Representation Learning

**요약** 본 연구는 IoT 환경에서의 단말기 이질성에 대응하기 위해 다중 채널 표현 학습 기반 Bluetooth RSS 위치추정 프레임워크를 설계하고 제안한다. 제안 방법은 고정 차원 fingerprint 벡터에 의존하는 기존 방식과 달리, 가변 길이 MAC 집합을 처리하며 RSS를 다중 채널로 확장하여 신호의 구조적 특성을 효과적으로 반영한다. 공개 OutFin 데이터셋을 이용한 실험 결과, 단일 단말기 환경에서 Top-1 및 Top-5 정확도 100%를 달성하여 k-NN, SVM, MLP 기반 기존 방법을 모두 상회하였다. 특히 교차 단말기 평가에서 기존 방법들이 최대 79% 이상의 성능 저하를 보인 반면, 제안 모델은 Top-1 정확도 93.74%를 유지하며 성능 감소폭을 6.26%로 제한하였다. 이러한 결과는 제안 프레임워크가 단말기 간 성능 저하를 효과적으로 완화하며, 실제 IoT 환경에서 안정적이고 일반화 가능한 위치추정을 제공함을 보여준다.

**주제어** : Bluetooth RSS 위치인식, 딥러닝 기반 위치추정, 디바이스 강건성, IoT 기반 위치추정 시스템, 표현 학습

## 1. Introduction

With the rapid growth of Internet of Things (IoT) technologies, localization has become a key enabling capability for applications such as smart logistics, autonomous robots, intelligent buildings, healthcare monitoring systems, and location-based services [1].

In healthcare environments, Bluetooth-based localization plays an important role in patient tracking, medical asset management, and elderly safety monitoring [2,3,4]. For example, accurate localization can enable real-time tracking of high-risk patients in smart hospital wards, where device heterogeneity and signal variability are inevitable. Among various approaches, Bluetooth Low Energy (BLE)-based positioning is widely adopted due to its low power consumption and ease of deployment.

Despite its advantages, a fundamental limitation of BLE-based localization lies in device heterogeneity. Even at the same physical location, RSS measurements may vary significantly depending on device-specific characteristics such as antenna design, receiver sensitivity, and hardware calibration, leading to severe performance degradation when models are transferred across devices.

To address this issue, this study adopts a representation learning perspective for Bluetooth received signal strength (RSS) modeling. Instead of using RSS as a single scalar input, we extend it into a multi-channel representation that captures complementary structural characteristics of signal observations. In addition, since BLE scans naturally produce variable-length and unordered MAC collections, we employ a set-based modeling strategy that directly processes such observations while preserving permutation invariance.

It is important to note that localization within a single device and environment is often a relatively well-posed problem, as RSS fingerprint patterns tend to remain stable under consistent conditions. Consequently, very high accuracy in

in-device settings does not necessarily indicate strong generalization capability, but rather reflects the intrinsic separability of fingerprint representations under fixed conditions.

Therefore, the primary objective of this study is not to further optimize in-device performance, but to address the more challenging and practically relevant problem of cross-device generalization.

Based on this design, we propose a device-aware Bluetooth RSS-based localization framework integrating multi-channel representation learning, attention-based token interaction, and hybrid multi-pooling aggregation. Token dropout is further introduced to improve robustness under partial signal observations.

Experiments conducted on the publicly available OutFin dataset demonstrate that while near-perfect performance can be achieved in in-device settings, the proposed approach significantly mitigates performance degradation under cross-device conditions, highlighting its robustness to device heterogeneity.

The remainder of this paper is organized as follows. Section II reviews related works, Section III presents the proposed method, Section IV describes experimental results, and Section V concludes the paper.

## 2. Related works

Conventional RSS-based localization methods typically construct fixed-length fingerprint vectors and apply machine learning classifiers such as k-nearest neighbors (k-NN), support vector machines (SVM), or multilayer perceptrons (MLP) [5,6,7]. While effective in controlled settings, these approaches often overlook device heterogeneity arising from hardware differences across Bluetooth terminals. Variations in receiver sensitivity, antenna gain and placement, RF circuit design, manufacturer-specific RSS calibration schemes, and signal filtering strategies can introduce systematic offsets or nonlinear distortions in RSS measurements

[8,9,10]. As a result, identical physical locations may produce substantially different RSS patterns when measured by different devices. This device heterogeneity becomes particularly problematic when models trained on one device are deployed on another, leading to significant performance degradation. Moreover, real-world BLE observations naturally form variable-length, order-invariant sets of detected MAC addresses, rather than fixed-dimensional vectors. Transforming such set-structured data into fixed-length representations may cause information loss and limit generalization performance.

### 3. Proposed Device-Aware Localization Framework

#### 3.1 Problem Formulation

In this study, BLE-based localization is formulated as a classification problem in which the input consists of a variable-length set of MAC observations. A single BLE scan contains a collection of detected MAC addresses along with their corresponding RSS values. The number of observed MAC addresses may vary across scans depending on environmental conditions and signal availability in practical IoT deployments.

Formally, a single BLE scan can be represented as an unordered set:

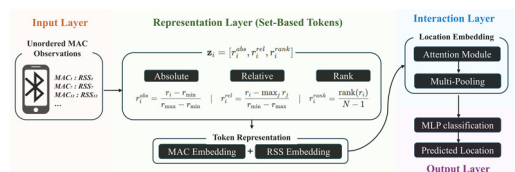
$$\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_N\}$$

where  $\mathbf{x}_i$  denotes the observation corresponding to the  $i$ -th MAC address, and  $N$  is the number of detected MAC addresses in a scan.

Unlike fixed-dimensional fingerprint vectors, BLE observations naturally form an unordered set structure. Since the detected MAC addresses do not possess inherent sequential ordering, the input should be treated as permutation-invariant. Therefore, the localization task aims to design a model capable of directly processing variable-length and unordered MAC observations while

learning stable and discriminative representations for position estimation.

The objective of this work is to develop a framework that preserves the original set structure of BLE scans rather than forcing them into fixed-length vectors. This formulation better reflects real-world IoT environments where signal availability is irregular and dynamic. Based on the above problem formulation, the overall architecture of the proposed set-based localization framework is illustrated in Fig. 1.



[Fig. 1] Overall architecture of the proposed device-aware localization framework.

#### 3.2 Multi-Channel Bluetooth RSS Representation

Conventional RSS-based localization approaches typically treat the RSS as a single scalar value for each observed MAC address. However, RSS measurements are highly sensitive to environmental dynamics, signal reflections, and device-specific characteristics. Representing RSS as a single value may therefore limit the expressive capacity of the model.

To address this limitation, we extend the scalar RSS into a multi-channel representation that captures complementary structural characteristics of signal observations. Specifically, each RSS measurement is decomposed into three components: an absolute normalized strength, a relative normalized strength within the same scan, and a rank-based feature reflecting the ordinal relationship among signals.

Formally, each observation is represented as:

$$\mathbf{x}_i = [x_i^{(1)}, x_i^{(2)}, x_i^{(3)}]$$

where  $x_i^{(1)}$ ,  $x_i^{(2)}$ ,  $x_i^{(3)}$  and denote the absolute, relative, and rank-based components, respectively.

The absolute component preserves global signal magnitude information by normalizing RSS values within a predefined range. The relative component emphasizes intra-scan relationships by encoding each signal strength with respect to the strongest signal observed in the same scan. The rank-based component captures structural ordering information by representing the relative position of each signal in the sorted strength sequence.

### 3.3 Set-Based Token Modeling

To preserve the natural structure of BLE observations, we adopt a set-based modeling approach [11] that directly processes variable-length collections of MAC signals. Each observed MAC address is converted into a learnable embedding vector, and the corresponding multi-channel RSS features are projected into the same embedding space.

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The token representation for each observation is defined as:

$$\mathbf{z}_i = \phi(\mathbf{x}_i)$$

where denotes  $\phi(\cdot)$  a learnable embedding function.

The resulting token set is expressed as:

$$\mathbf{Z} = \{\mathbf{z}_1, \dots, \mathbf{z}_N\}$$

These two representations are combined to form a unified token representation for each MAC observation.

### 3.4 Attention-Based Interaction Module

While individual token embeddings capture local signal characteristics, effective localization requires modeling relationships among signals

observed within the same scan. To capture such dependencies, an attention-based interaction module is introduced [12]. Through self-attention, each token dynamically refines its representation by incorporating contextual information from other tokens in the set.

To capture dependencies among observations, an attention-based interaction module is introduced. Through self-attention, each token dynamically refines its representation by incorporating contextual information from other tokens in the set.

The attention operation is defined as:

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^T}{\sqrt{d}}\right)\mathbf{V}$$

where Q, K, V are obtained from Z via linear projections.

### 3.5 Multi-Pooling Aggregation Strategy

After contextual refinement through attention, the token set must be aggregated into a fixed-dimensional representation for final classification. Instead of relying on a single pooling strategy, we employ a hybrid multi-pooling approach [13].

Mean pooling is defined as:

$$\mathbf{z}_{mean} = \frac{1}{N} \sum_{i=1}^N \mathbf{z}_i$$

Attention-based pooling is computed as:

$$\alpha_i = \frac{\exp(w^T \mathbf{z}_i)}{\sum_j \exp(w^T \mathbf{z}_j)}, \mathbf{z}_{attn} = \sum_{i=1}^N \alpha_i \mathbf{z}_i$$

The final representation is obtained by combining these features:

$$\mathbf{z}_{final} = [\mathbf{z}_{mean} \parallel \mathbf{z}_{attn}]$$

Attention pooling highlights informative tokens by assigning higher weights to important signals. Mean pooling captures the overall distribution of observed signals, while max pooling preserves the most strongly activated features.

### 3.6 Device-Robust Training Strategy

In real-world IoT environments, signal observations may fluctuate due to environmental dynamics or device-specific characteristics. To

enhance robustness under such variability, token dropout is applied during training [14]. Token dropout randomly removes a subset of input tokens, simulating partial signal loss and encouraging the model to avoid over-reliance on specific MAC observations.

#### 4. Experimental Setup

Experiments were conducted using the publicly available OutFin Bluetooth RSS dataset, which was collected in a real-world IoT environment [15]. The dataset consists of multiple reference points (RPs), where each sample corresponds to a BLE scan containing a variable number of MAC observations. Data were collected using two different mobile devices, enabling evaluation under heterogeneous device conditions.

For training and evaluation, data collected from Device A was randomly divided into training and validation sets using a 9:1 split ratio. The dataset from Device B was reserved exclusively for cross-device testing. This protocol reflects realistic deployment scenarios in which a localization model trained on one device is applied to another device with different signal characteristics.

Training was performed using the AdamW optimizer with early stopping based on validation accuracy. Token dropout was applied during training to enhance robustness under partial signal observations.

Localization performance was evaluated using Top-1 classification accuracy. In addition, Top-5 accuracy was reported to assess ranking stability. The proposed approach was compared with conventional RSS-based localization methods, including k-NN, SVM, or MLP models based on fixed-length fingerprint representations.

To provide a stronger comparison against recent deep learning approaches, we additionally implemented two attention-based baselines

inspired by recent indoor localization studies.

The first baseline was adapted from ABPN, which combines channel attention and spatial attention for wireless positioning [16]. Since the original ABPN was designed for CSI-based coordinate regression, we reformulated it for Bluetooth RSS fingerprint classification by using pivot-based RSS vectors and replacing the regression head with a classification head

The second baseline was adapted from DRVAT, which represents BLE observations as MAC-RSSI token sequences and applies self-attention to model latent relationships among beacons [17]. As the original DRVAT includes a semi-supervised pretraining framework and location regression, we retained its core supervised token-embedding and self-attention encoder structure while replacing the output layer with an RP classification head for fair comparison under our experimental setting. Table 1 summarizes the hyperparameter settings of all baseline models and the proposed model. All models were configured to ensure a fair comparison under the same experimental conditions.

(Table 1) Hyperparameter settings of baseline models and the proposed model

Model	Hyperparameters
k-NN	n_neighbors=5, weights="distance", metric="minkowski"
SVM	C=10.0, gamma="scale", kernel="rbf", probability=True
MLP	hidden_layer_sizes=(512, 256), activation="relu", alpha=1e-4, learning_rate_init=1e-3, max_iter=200
ABPN	input_channels=1, base_channels=64, Conv1d kernels=(7,5), channel_attention reduction=8, 3 residual blocks, 2 downsampling blocks, spatial_attention kernel=7, dropout=0.2, optimizer=AdamW, lr=1e-3, weight_decay=1e-4, batch_size=64, epochs=60
DRVAT	RSS bin range=[-110,-30], bin_step=5 dB, d_model=128, nhead=4, num_layers=2, dim_ff=256, dropout=0.1, max_len=256, pooling=masked mean, optimizer=AdamW, lr=3e-4, weight_decay=1e-4, batch_size=64, epochs=60
Proposed	multi-channel RSS (set-based tokens), d_model=256, nhead=4, num_layers=2, dim_ff=512, token_dropout=0.30, pooling=hybrid multi-pooling (mean + attention-weighted), label_smoothing=0.05, optimizer=AdamW, lr=3e-4, weight_decay=1e-4, batch_size=64, epochs=60

All experiments were implemented in Python 3.10.9 using PyTorch 2.0.1+cu117 on a Linux-based system (Linux 5.4.0-216-generic, x86\_64). Training was conducted on NVIDIA RTX A5000 GPUs with CUDA 11.7 and cuDNN 8.5.0.

## 5. Experimental Results and Analysis

### 5.1 In-Device Localization Performance

Table 2 presents the in-device localization results. The proposed model achieved near-perfect performance with Top-1 and Top-5 accuracy close to 100%, outperforming all baseline methods. While k-NN and MLP also showed strong performance (Top-1: 0.9836), and SVM achieved slightly lower accuracy (0.9754), the differences among methods are relatively small.

This observation indicates that in-device localization using RSS fingerprinting is inherently a relatively simple classification problem under fixed device and environmental conditions. The stability of RSS patterns within the same device and location leads to high separability between reference points, resulting in near-saturated performance across multiple methods.

Furthermore, given that the OutFin dataset consists of repeated scans collected within a limited time span at each reference point, the in-device setting does not involve significant temporal or environmental variability. As a result, very high accuracy in this setting should be interpreted with caution.

Therefore, the in-device performance reported in Table 2 should be regarded as an upper-bound reference under controlled conditions, rather than a definitive indicator of model robustness.

Nevertheless, the proposed model consistently achieves the highest accuracy among all methods, suggesting its strong discriminative capability within a controlled single-device environment.

(Table 2) In-device localization performance on Device A

Model	Top-1(%)	Top-5(%)
k-NN	0.9836	0.9918
SVM	0.9754	0.9836
MLP	0.9836	0.9918
ABPN	0.7235	0.9187
DRVAT	0.9590	0.9918
Proposed	1.0000	1.0000

### 5.2 Cross-Device Generalization Performance

Table 3 summarizes the cross-device localization performance. Compared to the in-device results in Table 2, traditional methods exhibit substantial performance degradation when applied to a different device. For instance, k-NN drops from 0.9836 to 0.0749 in Top-1 accuracy (-90.87%), and SVM decreases from 0.9754 to 0.1764 (-79.90%). MLP also shows a notable reduction from 0.9836 to 0.6359 (-34.74%).

To further strengthen the comparison, we additionally evaluated two recent attention-based deep learning baselines (ABPN-inspired and DRVAT-inspired).

Although these models incorporate more advanced feature learning mechanisms, they also exhibit noticeable performance degradation under the cross-device setting. Specifically, the ABPN-inspired model achieves 0.2410 Top-1 accuracy, while the DRVAT-inspired model shows a significantly lower performance of 0.0503.

These results indicate that simply adopting attention-based architectures does not guarantee robustness to device-induced distribution shifts. Instead, they highlight that cross-device generalization remains a challenging problem that cannot be effectively addressed by model complexity alone.

This severe degradation is primarily attributed to distribution shifts in RSS measurements across devices, caused by differences in hardware characteristics such as antenna configuration, receiver sensitivity, and signal processing pipelines.

Conventional fingerprint-based methods, which rely on fixed RSS representations, are particularly vulnerable to such discrepancies.

In contrast, the proposed model maintains strong generalization capability, with Top-1 accuracy decreasing only from 1.0000 to 0.9374 (-6.26%) and Top-5 accuracy from 1.0000 to 0.9836 (-1.64%).

It is important to note that, unlike in-device evaluation where performance may be saturated due to stable signal patterns, cross-device evaluation introduces a more realistic and challenging scenario involving distribution shift. Therefore, the results in Table 3 provide a more meaningful assessment of model robustness.

The superior performance of the proposed method suggests that multi-channel RSS representation and set-based modeling enable the model to capture relatively device-invariant structural characteristics of signals, rather than overfitting to device-specific RSS patterns.

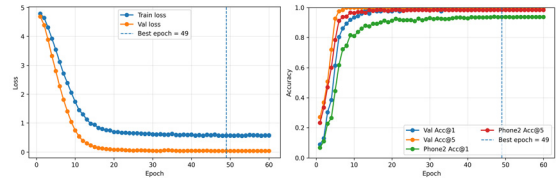
These results demonstrate that the proposed approach effectively mitigates cross-device performance degradation and achieves robust localization across heterogeneous devices.

⟨Table 3⟩ Cross-device localization performance on Device B

Model	Top-1(%)	Top-5(%)
k-NN	0.0749	0.1559
SVM	0.1764	0.1897
MLP	0.6359	0.8010
ABPN	0.2410	0.3651
DRVAT	0.0502	0.2328
Proposed	0.9374	0.9836

Fig. 2 illustrates the training dynamics of the proposed model, including loss and accuracy trends across epochs. The model converges rapidly within the early training stage and remains stable without noticeable overfitting. Validation Top-1 and Top-5 accuracies steadily improve and saturate near convergence, while

cross-device performance on Phone2 follows a similar upward trajectory, indicating strong generalization capability. The best model was selected at epoch 49 based on validation Top-1 accuracy with loss-based tie-breaking.



[Fig. 2] Training dynamics of the proposed Bluetooth Set Transformer model. (Left) Training and validation loss curves over epochs. (Right) Top-1 and Top-5 accuracy trends on the validation set and the cross-device Device B(Phone2) dataset.

### 5.3 Ablation study

Table 4 presents the ablation results focusing on the key components of the proposed model. Removing the multi-channel RSS representation reduced the cross-device Top-1 accuracy from 0.9374 to 0.9077, while removing the attention-based interaction module further decreased it to 0.9036.

⟨Table 4⟩ Ablation results of the proposed model under in-device and cross-device settings.

Model	In-device Top-1(%)	Cross-device Top-1(%)
Proposed	1.0000	0.9374
w/o multi-channel	1.0000	0.9077
w/o attention	1.0000	0.9036

## 6. Conclusion

This paper presented a device-robust Bluetooth RSS-based localization framework based on multi-channel representation learning and set-based modeling for IoT environments. By extending scalar RSS measurements into structured multi-channel representations and directly processing

variable-length MAC observations, the proposed framework effectively captures the structural characteristics of BLE signals.

Experimental results on the OutFin dataset showed that near-perfect accuracy can be achieved in in-device settings; however, this result primarily reflects the intrinsic simplicity of RSS fingerprint-based localization under fixed device and environmental conditions rather than true generalization capability.

More importantly, under cross-device evaluation, the proposed model significantly mitigates performance degradation compared to conventional fingerprint-based approaches, maintaining strong localization accuracy across heterogeneous devices.

These findings highlight that addressing device heterogeneity is essential for practical BLE-based localization systems, and that robust representation learning plays a key role in achieving this goal. Therefore, the main contribution of this work lies in improving cross-device generalization rather than optimizing in-device performance.

The proposed framework has strong potential for healthcare-oriented IoT applications, such as patient tracking, smart hospital monitoring, and elderly safety management, where device heterogeneity and signal variability are common.

However, the current evaluation is limited to a two-device setting, and thus does not fully capture the diversity of hardware variations encountered in real-world deployments. Future work will focus on extending the evaluation to multiple devices and more diverse environments to further validate the generalization capability of the proposed framework.

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