

Investigation and Enhancement of Outdoor Localization Using RSSI Analysis and Gateway Positioning

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Abstract—is fake: Localization of a device in smart cities has become a challenging problem. The number of Internet of Things (IoT) devices connected to Low-Power Wide-Area Networks (LPWANs) forces network operators to improve the scalability of their networks. Additionally, these mobile devices are typically powered by a small battery that must last for several years. Sensors reporting air quality and smart water level sensors are just examples of the growing need for device localization throughout the city. This paper investigates the impact of Received Signal Strength Indicator (RSSI) on the quality of model learning and proposes a method to enhance localization performance through gateway positioning and RSSI analysis.

Index Terms—RSSI, LPWAN, Sigfox, Localization, IoT.

I. INTRODUCTION

Localization of a device in smart cities has become a challenging problem. The number of Internet of Things (IoT) devices connected to Low-Power Wide-Area Networks (LPWANs) forces network operators to improve the scalability of their networks. Additionally, these mobile devices are typically powered by a small battery that must last for several years. Sensors reporting air quality and smart water level sensors are just examples of the growing need for device localization throughout the city. The increasing importance of the Internet of Things (IoT) has created a demand for extensive communication standards that ensure reliable connectivity between many IoT devices. To this end, researchers have developed various LPWAN standards. The IoT requires LPWAN standards to support long-range communications and high scalability of end devices at a low cost. Also, ubiquitous connectivity indoors and outdoors as well as ultra-low power consumption are critical aspects for reliable and transparent IoT applications that run for years on small batteries [1*]. LPWANs have emerged as an alternative to traditional Global Navigation Satellite System (GNSS) receivers because GNSS receivers consume a lot of energy. Additionally, satellite-based solutions face limitations in indoor environments as signals do not pass well through walls. Among common LPWAN technologies, Sigfox, LoRaWAN, and NB-IoT are the most prominent [10*]. While NB-IoT operates in licensed bands with low latency, Sigfox and LoRaWAN show advantages by

leveraging greater range and longer battery life [7*]. Context awareness is one of the critical aspects of Internet of Things (IoT) applications. This concept means that IoT devices can change their behavior based on environmental measurements. For this awareness, accurate device localization is essential. Currently, Global Navigation Satellite System (GNSS) is the most common method for this purpose. However, GNSS has limitations that do not align with IoT needs. Firstly, GNSS receivers consume a lot of energy, which reduces battery life [3]. Secondly, GNSS location data is only available on the device itself, and sending it to the network requires more energy. In contrast, wireless positioning techniques that use LPWAN communications eliminate the need to transmit additional location data and reduce energy consumption. Also, GNSS systems face connectivity issues in indoor environments, while many LPWAN standards operate in sub-gigahertz ISM bands and are usable in both indoor and outdoor environments.

There are several methods for determining the location of a transmitting device in an LPWAN. In each approach, a trade-off must be made between location accuracy and energy consumption. However, when comparing different studies from one approach, several other parameters must be considered. For example, the cost and effort of training a model or installing equipment should be taken into account. Additionally, the indoor or outdoor environment and the number of receiving gateways also play a crucial role in the achieved localization accuracy [8*]. For Time Difference of Arrival (TDoA) and Angle of Arrival (AoA) approaches, gateways and antennas must be synchronized respectively. Several advanced TDoA algorithms are compared in [6*]. TDoA-based positioning and tracking with LoRaWAN are discussed in [9*].

In this article, we address the impact of the Received Signal Strength Indicator (RSSI) and its effect on the quality of model learning, and by prioritizing these values, we improve the used model. Wireless localization has been a prominent research topic for decades [4-6]. Many techniques developed over the years are still suitable for localization with modern wireless technologies. These techniques estimate the location of a transmitter or receiver by analyzing physical characteristics of the communication link such as received signal strength (RSS),

timing information, signal phase, etc. One of these methods is RSS-based fingerprinting. With this method, a training database of communication messages is created by storing the location of their transmitter along with the received signal strength indicator (RSSI) for all receiving base stations. Then, RSSI measurements of new messages are matched with the fingerprints in the training database to estimate the location of the transmitter, for example, using k-nearest neighbor (kNN) analysis, probabilistic methods, support vector machines, decision trees, etc. [5*]. The main advantage of fingerprinting is that the locations of base stations do not need to be known. To minimize location estimation error, an extensive site survey must be conducted to create a complete training database. Therefore, fingerprinting techniques are more commonly used in enclosed and indoor areas [7,8]. RSS-based fingerprint localization in outdoor environments can be challenging given the time and effort required to create the training database and the dynamic environment of a city. However, Aernouts et al. successfully collected a large amount of RSS samples along with GPS coordinates as ground truth data in the city of Antwerp, Belgium [1*]. Both Sigfox and LoRaWAN messages were collected.

II. RELATED WORK

Grigorios G. A. et al. [A Reproducible] discuss the critical preprocessing steps and the model used for outdoor localization utilizing RSSI fingerprinting within the Sigfox network. These steps are essential for optimizing performance. The preprocessing stage encompasses several key activities aimed at preparing raw data for effective analysis. This includes addressing out-of-range values by replacing extreme RSSI values (e.g., -200 dBm) with a more realistic minimum value derived from the training set. Additionally, various data transformation techniques are applied to enhance the input data quality, such as adjusting RSSI readings to remove negative values by subtracting the minimum RSSI value from all inputs. The model employed in this study is based on the k-nearest neighbor (kNN) algorithm, a widely-used method for classification and regression tasks. In this context, the kNN algorithm is applied for localization by comparing new RSSI measurements against a database of known fingerprints. The authors conduct a comprehensive evaluation of various distance measures (e.g., Euclidean, Manhattan) to identify the most suitable one for their dataset. Moreover, the hyperparameter k , which determines the number of nearest neighbors to consider, is fine-tuned to optimize the model's performance. Michiel Aernouts et al. [A Comparison] present a significant advancement in localization methods for Internet of Things (IoT) applications by comparing different signal strength-based localization techniques, specifically using Sigfox communication messages. The authors conducted experiments in an urban environment, collecting a comprehensive dataset via Stickntrack devices that transmit GPS coordinates through Sigfox. They evaluated three proximity-based algorithms, a fingerprinting method, and three ranging methods, assessing the effectiveness of these approaches in estimating the location of IoT devices

while considering the trade-off between accuracy and battery life. Notably, the fingerprinting method proved to be the most accurate. This research not only validates the use of diverse hardware for localization but also provides a robust dataset for future studies. This contributes to the development of low-power, long-range localization solutions that can operate effectively both indoors and outdoors. The findings underscore the potential of utilizing existing communication links in LPWANs, such as Sigfox, to enhance location-based services. Grigorios G. Anagnostopoulos et al.[A Reproducible Comp...]. provide a detailed comparison of machine learning methods for outdoor RSSI fingerprinting, establishing key benchmarks for localization accuracy in real-world settings. Using a dataset from urban LoRaWAN RSSI measurements in Antwerp, they address challenges such as signal attenuation, environmental variability, and GPS inaccuracies. By highlighting RSSI fingerprinting as an alternative to GPS-based methods, they contribute to more robust outdoor positioning systems. Their focus on reproducibility, with publicly available datasets and code, encourages further research and innovation in IoT-based localization. Mahnoor Anjum et al.[Analysis of RSSI Finge...]. significantly advance wireless localization by applying LoRa technology to RSSI fingerprinting, extending its use from indoor to outdoor settings. Their research integrates environmental factors to enhance accuracy and provides an in-depth analysis of path loss characteristics, offering new insights into signal propagation in diverse environments. The dataset, consisting of 16,811 RSSI readings collected with a Dragino LG01 LoRa Gateway and a LoRa End Device across different building floors, includes both line-of-sight and non-line-of-sight conditions. This comprehensive dataset supports robust modeling of RSSI-to-distance relationships, improving the reliability of localization systems and highlighting LoRa's potential for scalable and effective positioning solutions in real-world scenarios. Irfan Fachrudin Priyanta et al.[Evaluation of LoRa Te...]. make a notable contribution by exploring the application of LoRa technology for tracking vehicles and assets in smart harbors, addressing the challenges of harsh industrial environments and limited network infrastructure. Their research is distinguished by its focus on the specific conditions of seaports, where traditional networks like LTE or 5G are often unavailable. They utilize LoRa's long-range, low-power capabilities to propose a real-time tracking system, supported by extensive ns-3 simulations to assess data transmission rates, scalability, and coverage. Although the study does not use a traditional dataset, the simulation-based evaluation with parameters such as node configurations and performance metrics provides a robust analysis of LoRa's effectiveness in port environments. This work contributes significantly to smart harbor initiatives by offering insights into optimizing asset and vehicle tracking systems in challenging industrial settings. Azin Moradbeikie et al.[Improving LoRaWAN R...]. significantly enhance localization techniques by applying LoRaWAN for tracking in harsh harbor environments, an area previously underexplored. Their research includes a real-world implementation of a LoRaWAN-based system, addressing

the challenges posed by dynamic conditions such as large metal structures and varied land surfaces that impact RSSI measurements. They develop a multi-slope path-loss model to improve localization accuracy and outline future research directions for refining these methods. The dataset, collected from a harbor-scale LoRaWAN testbed over three days, captures RSSI data in various dynamic scenarios, supporting the evaluation of different localization techniques and path-loss models. This empirical data underpins their contributions to robust localization in complex environments. Wongeun Choi et al [Low-Power Lo..]. make a significant contribution by proposing a novel outdoor positioning method that utilizes LoRa signals in conjunction with a fingerprinting algorithm, effectively addressing the limitations of traditional GPS-based systems. Their approach offers a low-power, cost-effective solution that is particularly suitable for IoT applications, such as tracking people and animals. The authors conduct extensive experiments using a dataset collected from a 340m x 340m area, where four LoRa gateways recorded RSSI values to create detailed fingerprint maps. This dataset includes RSSI measurements, GPS coordinates, and metadata, enabling a robust evaluation of the positioning method. This work is significant in advancing energy-efficient and practical localization solutions in IoT environments. Ramon Sanchez-Iborra et al [Tracking and Mon...]. make a noteworthy contribution by developing a LoRa-based tracking and monitoring system for lightweight boats, specifically tested in a real-world maritime environment. Their work is distinguished by its innovative use of LoRa technology to enhance tracking capabilities for sailboats, addressing both practical and technical challenges in coastal settings. The study employs a comprehensive dataset collected during experiments in the port of Vigo, Spain, using sensors on Optimist Class sailboats. This dataset includes GPS coordinates, environmental metrics, and boat dynamics data, transmitted using LoRa with varying configurations to assess performance. The collected data reveals insights into the system's range, packet delivery reliability, and power consumption, demonstrating its effectiveness and efficiency in tracking and monitoring under real maritime conditions. The dataset and experimental results underscore the potential of LoRa technology for marine applications, offering valuable benchmarks for similar future endeavors.

III. MATERIAL AND METHOD

A. Proposed Method

First, the data is thoroughly analyzed using a coverage analyzer. The output of the analyzer consists of a series of paired values, where the first value represents the index of useful gateways, and the second value corresponds to the section in which the gateway exhibits significant performance. These paired values, along with the input data, are then processed through a feature extraction mechanism to extract data specific to each section. This extracted data is subsequently input into a section system that identifies the optimal sections. The model is then trained based on the identified sections, with data from each section fed into the corresponding section-specific model

to produce the desired output. The complete flowchart of this system is presented in Figure 1.

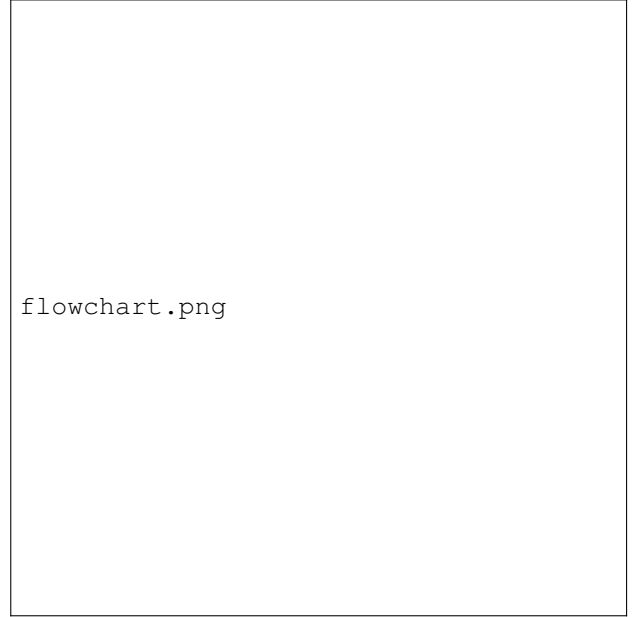


Fig. 1. System flowchart for the proposed method.

IV. RESULTS

Table I summarizes the performance metrics of the proposed model compared to other methods.

TABLE I
COMPARISON OF LOCALIZATION RESULTS

Method	Mean Error [m]	Median Error [m]	R ² -score
Michiel Aernouts et al. [?]	214.58	15.4	–
Proposed Method	–	–	–

V. DISCUSSION

VI. FUTURE WORK

REFERENCES