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Improving LoRaWAN RSSI-Based Localization in Harsh Environments: The Harbor Use Case

Azin Moradbeikie[1,2], Ahmad Keshavarz[1], Habib Rostami[1], Sara Paiva[2], and Sérgio Ivan Lopes[2,3,4](✉)

[1] PGU—Persian Gulf University, Bandar Bushehr, Iran
{amoradbeiki,a.keshavarz,habib}@pgu.ac.ir
[2] ADiT-Lab—Instituto Politécnico de Viana do Castelo, Rua Escola Industrial e Comercial NunÁlvares, 4900-347 Viana do Castelo, Portugal
spaiva@estg.ipvc.pt
[3] CiTin—Centro de Interface Tecnológico Industrial, 4970-786 Arcos de Valdevez, Portugal
sil@estg.ipvc.pt
[4] IT—Instituto de Telecomunicações, 3810-193 Aveiro, Portugal

Abstract. Recently, LoRaWAN communications have become a widely used technology within IoT ecosystems due to their long-range coverage, low-cost, and native RSSI-based location capabilities. However, RSSI-based localization has low accuracy due to interference in propagation, such as the multipath and fading phenomena, becoming more critical in harsh and dynamic environments like airports or harbors. A harbor has a wide area with a combination of distinct landscapes (sea, river, urban areas, etc.), and distinct infrastructures (buildings, large steel structures, etc.). In this paper, we evaluate and present a harbor assets localization system that uses a LoRaWAN-based multi-slope path-loss modeling approach. For this purpose, a harbor scale LoRaWAN testbed, composed of three gateways (GWs) and a mobile end node, has been deployed and used to characterize RSSI-based multi-slope path-loss modeling under realistic conditions. Experimental data have been collected over three days in different dynamic scenarios and used for ranging and location estimation comparison using distinct methods, i.e., RSSI-based and fingerprinting. Based on the achieved results, by a correct partitioning of the test environment based on its specific environmental conditions, a decrease between 4 and 10 dBm in path-loss estimation error can be achieved. This path-loss estimation error decrements provide 50% improvement in distance estimation accuracy.

Keywords: IIoT · LoRaWAN · RSSI · Fingerprinting · Localization

1 Introduction

Due to the steady development of cities and industries in recent years, the demand for goods transportation for industrial and manufacturing as part of

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supply chains has increased. Harbors act as the primary player in supporting and managing the global import and export of goods. According to the Trans-European Transport Network (TEN-T) report [1], 74% of the goods imported and exported and 37% of exchanges within the European Union transit through harbors. Furthermore, Asia dominates the global maritime trade arena, with 41% of goods loaded and 62% of goods unloaded. The increase of the maritime trade area drives the harbor to continue to rely on a sustainable expansion of promising technologies [2], such as Industrial Internet of Things (IIoT), Big Data, Cloud Computing, and communication technologies, and thus move towards a smart harbor, and thus promoting process optimization and sustainability.

Due to the large area of ports and continuous long-time operation requirements of assets, the adopted communication network should provide long-range coverage with low power consumption to provide an energy-efficient solution. These requirements make newly emerged LPWAN (Low Power Wide Area Networks) technologies — such as Sigfox, LoRa, and NB-IoT—an appropriate candidate for communications within the smart harbor. Between these technologies, LoRaWAN features (long range, easy deployment, increased battery life, cost efficiency, and reduced latency) [3] make it a potential solution for secure end-node communication in the IoT ecosystem [4], and thus provide cost-effective Location-Enabled IoT (LE-IoT). In addition, a smart harbor needs robust and reliable localization and tracking methods to provide efficient harbor management by supporting decision-making [5,6].

Received Signal Strength Indicator (RSSI), Time of Arrival (ToA), and Angle of Arrival (AoA) are the three main methods for signal feature-based localization. ToA and AoA methods need costly hardware, which makes them expensive solutions for harbor because of the need for extensive and high number deployment. On the other hand, RSSI-based localization has become the most cost-effective option for end-node localization, however, it faces several relevant challenges in the harbor. In the RSSI localization method, the attenuation of RF signals is used for distance estimation based on a prior known path-loss model. The estimated distance is then used in the location estimation of the end node. Since LoRaWAN technology enables long-distance communication, an end node can be in near or far and in different directions of a gateway (GW). So, it will experience different power attenuation due to distinct environmental situations and different types of land surfaces and weather conditions (such as temperature and humidity) [7]. Moreover, high environmental dynamics (led by moving vessels, quay cranes, terminal tractors, containers, etc.) make it hard to determine a static path-loss model for the harbor. For example, when a vessel arrives at a harbor, containers are unloaded from it and moved to the yard of the harbor (temporary storage area for containers). Unloading containers to the yard is similar to the sudden creation of a building in the harbor. This sudden change leads to changes in signal path loss. In addition, a multitude of metallic components and surfaces and the fading effect resulting from the sea proximity, make harbors harsh environments for using RSSI-based localization methods. Furthermore, as the localization of containers in the harbor is an important requirement, the adopted method for location estimation should be low power consumption. Encouraged by the aforementioned challenges, this paper, at first, describes a LoRaWAN architecture for harbor assets locating and provides an evaluation of the environment dynamic effect on the distance estimation error. Next, a detailed characterizing of path-loss measurements in various roads of harbor caused by distinct environmental situations (such as Line-of-Sight and Non-Line-of-Sight effects and different types of land surfaces) is presented to prove the importance of multi-slope path-loss model consideration for accuracy improvement.

The remainder of the paper is organized as follows: Sect. 2 reviews related work, Sect. 3 describes the deployed LoRaWAN testbed architecture used in the experimental procedure, in Sect. 4 the results are presented, and lastly, in Sect. 5 conclusions are put forward.

2 Related Work

There is a growth in research to provide an end node localization method as a substitute for Global Navigation Satellite Systems (GNSS) because of their higher power consumption and higher operational cost. In February 2015, the LoRaWAN Alliance released a Long-Range Wide Area Network (LoRaWAN) geolocation white paper. LoRaWAN uses the LoRa Chirp Spread Spectrum (CSS) modulation method that provides long-range coverage [8]. Several existing works provide measurements of the LoRa technology performance as a communication protocol (including coverage, capacity, delay, and throughput) in various applications [10,11,13,14]. In [10], the authors measure the coverage performance of LoRaWAN in an urban area. Their results show that the amount of successfully delivered packets exceeds 80% for up to 5 km distances. Authors in [11] introduce setups of the performance measurements to analyze the scalability of the LoRaWAN. They realized that more than 60% of the packets can be received from a distance of up to 30 km on water.

Industrial environments are one of the most challenging cases for LoRa usage. In [13], the authors evaluate the performance of a LoRaWAN network in industrial scenarios. In the proposed model, different IIoT end nodes communicate with a central controller to provide monitoring and sensing information. For this purpose, they use the NS-3 *lorawan* module as a simulator for their evaluation. Authors in [16] demonstrate the feasibility of a LoRaWAN to be used for data collecting in marine environments. In the proposed model, the transmitting device is placed in the middle of the sea and the gateway is placed ashore. They set up an operating network and proved that the best SF to be exploited for the whole system is 7 since it ensured limited packet losses. Authors in [17] propose a real-time monitoring infrastructure for the remote, real-time control of offshore sea farms based on LoRaWAN by using Fixed Nodes and Mobile Sinks. However, authors in [18] show that the floating LPWAN suffers significant performance degradation, compared to the static terrestrial deployments. They present a novel channel access method for floating LPWAN. In [19], present a new method for communicating and auto-adapting to the altering requirements and typical conditions of a marine environment based on LoRaWAN protocol to routinely transfer data between the open sea and the land. In the all mentioned papers, the authors adopt LoRaWAN just as a communication network and not for localization and tracking purposes.

Localization and tracking are one of the interesting uses of LoRaWAN. In [9], the feasibility of LoRaWAN adoption for a GNSS-less localization has been proved. In [15], the authors present a boat tracking and monitoring system based on LoRa. Their obtained results showed the validity of LoRa aiming at ships tracking in port. In [20], the authors evaluated the scalability of LoRa devices in the network of the LoRa radio technology for geolocation and tracking using ns-3 for a harbor use case. They mention that, if 500 nodes are deployed in an area spanning a radius of 2500 m, the probability of successful transmission is greater than 85%. They do not provide a real case of study, but they stated to derive the appropriate LoRaWAN implementation in harbor application, its parameters (like SF value, number of nodes, update rate, and coverage area) have to be determined accordingly. Despite the growing research in LoRa-based networks and localization methods, there is still a need for further development and evaluation of LoRaWAN in industries with harsh environments. In this paper, we set up a real implementation of LoRaWAN for harbor asset tracking in an industry with a harsh environment.

3 LoRaWAN Experimental Testbed

In this section, we present the components and the architecture of the LoRaWAN testbed, which consists of three deployed LoRaWAN gateways (one on the rooftop of the harbor central building and two more on the Telecommunication tower) and one end node that is moved across the Bushehr harbor. As the localization accuracy in the up part of the harbor is most important for the company, the location of GWs are chosen in such a way as to provide triangulation of GWs for the up part of the harbor. The distance of GW1 from GW2 and GW3 is equal to 790 m and 920 m, respectively. The topology of the LoRaWAN testbed and its surrounding environment is illustrated in Fig. 1.

Each gateway is equipped with an MCU and an SX1301 digital baseband transceiver and has been installed on antenna towers with heights between 30 and 35 m (Fig. 1). The LoRaWAN end node is implemented with an MCU, a transceiver SX1276, and a GPS unit mounted on the roof of a car with a height equal to 1.5 m (Fig. 1). While the car is moving in the harbor, the LoRaWAN end nodes will transmit packets to the gateways at intervals of 9 s. A packet includes GPS coordinates, timestamps, and battery charge information. The corresponding SNR and RSSI of the end node are also transmitted to the gateways.

All the packets are transmitted with a spreading factor, bandwidth, coding rate, and channel equal to 7, 125 kHz, 4/5, and 868 kHz respectively. All the data were collected in the harbor area from Feb 6, 2022, to Feb 15, 2022. We logged over 2500 records sensed by at least two gateways in total. The collected is depicted with red points in Fig. 2.

4 Evaluation Results

Harsh and high dynamics of the harbor environment leads to vast changes in PL parameters and measured RSSI subsequently. This issue caused high variance in measured RSSI for the same location which makes RSSI-based localization methods so challenging. For showing this problem, in this paper, experiments took place in two different situations (busy and solitude days in the harbor). The variance of measured RSSI based on distance from GW1 on these different days is shown in Fig. 3.

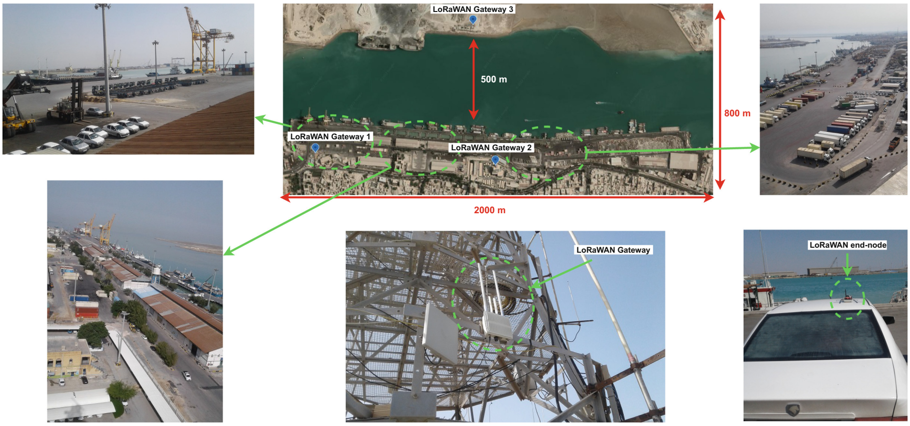


Fig. 1. Harbor LoRaWAN testbed with Gateways with an end node identified.

Fig. 2. Spatial data collected with the LoRaWAN testbed.

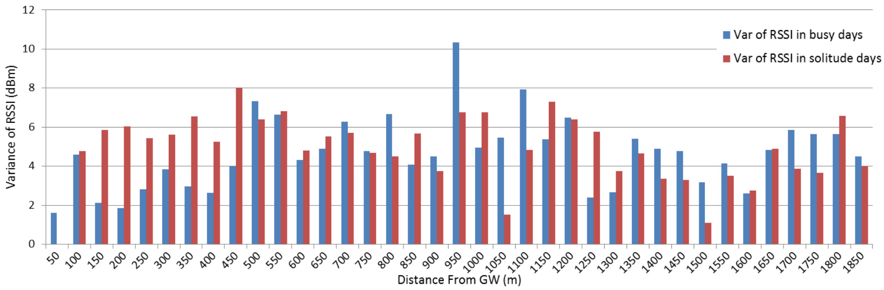


Fig. 3. The variance of measured RSSI-based on distance from GW1 in busy and solitude days.

On a busy day, a vessel anchored in a specific terminal leads to increase truck traffic in the yard between GW1 and GW2 to unload containers from the vessel. These dynamics force the environment to experience several radio propagation phenomena, e.g., multipath, fading and interference, impacting the variance of the received and measured RSSI values, showing distinct patterns for busy and solitude days. Several RSSI measurements for the same distance from a GW, on different days, increase the overall localization error. This variance can also be seen for distances of less than 500 m, cf. Fig. 3. Moreover, there are also similar changes in the RSSI variance measured by GW2 which indicates that these propagation-related phenomena occur all around the harbor.

In the following of this section, the accuracy of distance estimation by using a single PL model is presented and the improvement scale of estimated distance by using a multi-slope PL model is reported. Then, location estimation accuracy by using the fingerprint method is presented.

4.1 Distance Estimation by Using Single PL Method

To compute the distance estimation accuracy in the harbor, first, we used the measured RSSI to calculate the path-loss by using Equation (1).

$$PL = RSSI + SNR + P_{tx} + G_{tx} \tag{1}$$

where SNR represents the signal-to-noise ratio (dB), P_{tx} is the transmission power, and G_{tx} corresponds to the gain of the transmitter. The measured PL (dBm) data can be conveniently modeled using the first-order fit to compute the path loss model as Eq. (2).

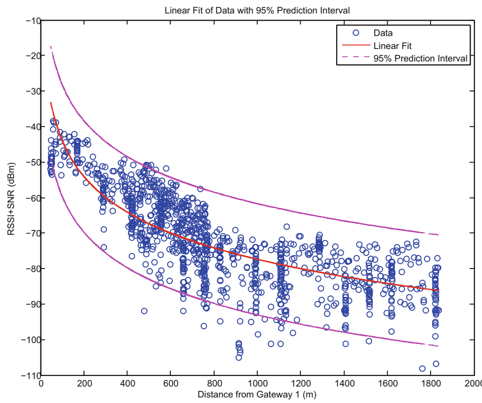


Fig. 4. Measured and expected path-loss in a Busy day.

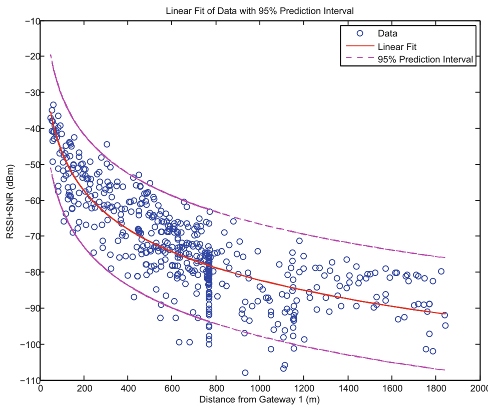


Fig. 5. Measured and expected path-loss in a Solitude day.

$$PL = A + 10nLog(d) \tag{2}$$

where n is the path loss exponent, A is the path loss value at a reference distance equal to one meter from the receiver, and d is the distance between an end node and the LoRaWAN gateway [12]. Figure 4 and 5 show the measured path loss (marked with blue dots) and the expected path loss of GW1 (solid red curve) for a busy and solitude day in the harbor, respectively. The PL diversity leads to various path loss exponents on busy and solitude days. There is the same situation for GW2. The calculated path loss exponents and average distance estimation error of three GWs are listed in Table 1.

4.2 Distance Estimation by Using Multi-slope PL Method

As mentioned, end nodes at the same distance, but in different directions of a gateway will experience different power attenuation due to distinct environmen-

Table 1. Path-loss characteristics obtained experimentally.

Gateway ID	Measurement Scenario	n	A	Average Distance Estimation Error
GW1	Busy day	3.329	22.58	805.5 m
	Solitude day	5.557	24.51	678.8 m
GW2	Busy day	0.9815	40.08	412.0 m
	Solitude day	1.4271	31.09	462.9 m
GW3	Busy and Solitude day	6.4	102	761.3 m

tal conditions (Line-of-Sight and Non-Line-of-Sight effect) and different types of land surfaces.

On this basis, it is important to provide an optimum environment partitioning and compute the path-loss model for each partition. To evaluate the effect of distinct environmental conditions on the path-loss, the collected data for a specific part of the harbor (Fig. 6, (a)) is split into two distinct sets (Fig. 6, (b) and (c)).

The selected data in Fig. 6, (b) and (c) has the same distance from GW1. But, they have various environmental situations (Fig. 6, (b) has less than 10 m distance from sea and Fig. 6, (c) surrounded by high buildings that lead to the loss of the Line-of-Sight effect in some parts). Figure 7 shows the measured path loss (marked with blue dots) and the expected path loss (solid red curve) for specified parts in Fig. 6, respectively. As it can be seen in Fig. 7, by dividing the environment into two parts, the data samples in Fig. 6, (a) are split into two parts such that it leads to a decrease in the difference between estimated and measured path loss. This results in a decrease in the average distance estimation error and improves distance estimation accuracy. The two slope path-loss model can be presented as Eq. 3.

$$PL = A_i + 10 n_i Log(d_i), \quad i = 1, ..., k \cap d_i \subseteq Part_i \tag{3}$$

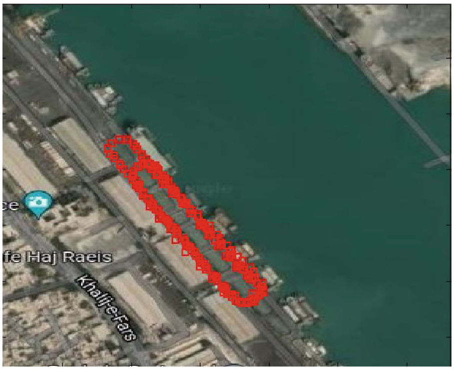
where $i = 1, 2, ..., k$ is equal to the number of considered parts of the divided environment. The calculated two slope path loss exponents for the split parts are listed in Table 2. Based on the result, for distance estimation improvement, it is important to consider the multi-slope path-loss model.

Table 2. Two slope path-loss characteristics obtained experimentally.

#	Near to the Sea		Near to the Buildings	
	n	A	n	A
GW1	5.221	83.128	2.602	0.84
GW2	1.886	17.675	1.954	21.94
GW3	1.946	117	2.637	116

4.3 Location Estimation by Using Fingerprint Method

The accuracy and usability of the fingerprinting algorithm implementation for large areas of the harbor for localization are presented in this subsection. We estimated the locations of the end node by using the fingerprint method on each busy and solitude day separately. For this purpose, the environment is split into 5×5 m squares. The location of the end node is estimated based on the constructed radio map of the harbor on the same day. The average location estimation error is equal to 346 m. The most important drawback of the fingerprint-based localization method is its requirement for frequent signal map updating. As the harbor has a highly dynamic environment, the requirement for signal map updating becomes a huge problem that makes it an inappropriate method.

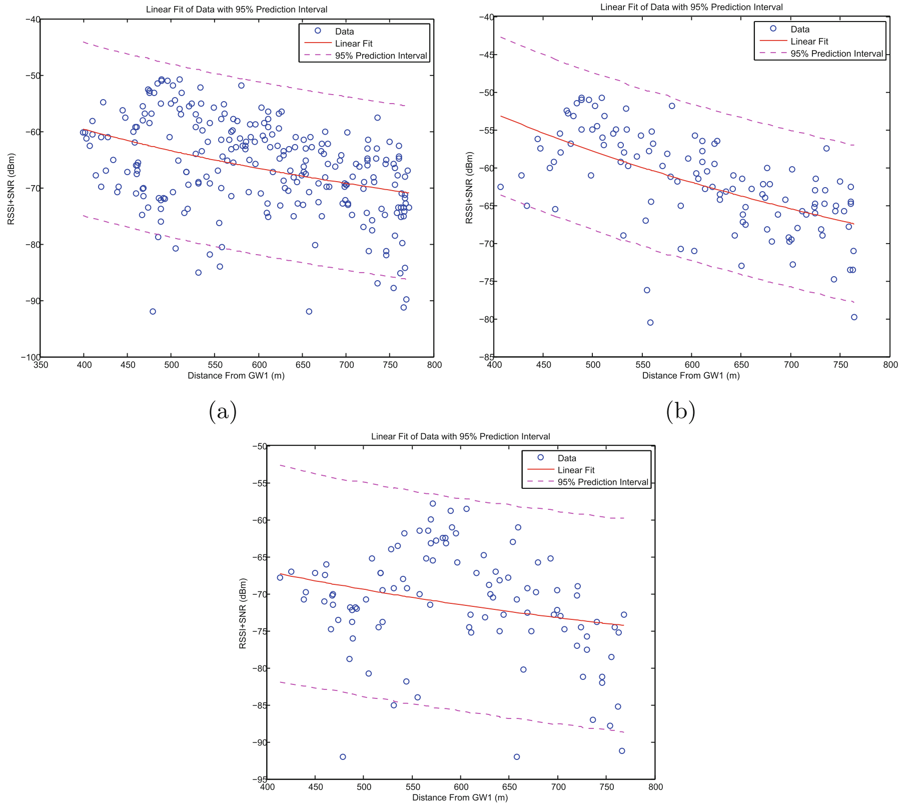


(a)

(b)

(c)

Fig. 6. Selected part of the harbor for distinct environmental situations effect evaluation: a) all data points; b) less than 10 m distance from the sea; and c) surrounded by high buildings and losing the Line-of-Sight effect in some parts.



(a) (b) (c)

Fig. 7. Selected part of the harbor for distinct environmental situations effect evaluation: a) all data points; b) less than 10 m distance from the sea; and c) surrounded by high buildings and losing the Line-of-Sight effect in some parts.

According to the stated contents, based on the highly dynamic environment of the harbor, RSSI-based localization is a more efficient method. There are many RSSI-based localization methods. An overview of localization methods using RSSI in public LoRaWan is presented in Table 3. But these methods are executed in normal environments and it is necessary to customize these methods to provide an acceptable localization accuracy in highly dynamic environments.

Table 3. An overview of localization methods using RSSI

Method	ANN [21]	ANN [22]	Linear Ridge [23]
Localization accuracy	340 m	381 m	784 m

5 Conclusion

In this paper, the implementation of a LoRaWAN-based localization system for a harbor has been described, and the experimental characterization of its harsh environment. Based on the authors' knowledge, it is the first paper that reviewed the high dynamics effect of the harbor on RSSI-based localization by using LoRaWAN. Results have shown that fingerprint-based localization has better performance (346 m) which is not acceptable for the harbor environment. Furthermore, its accuracy depends highly on the completeness of generated radio map information for the target area. In addition, updating the radio map is an important issue that decreases its performance. On the other hand, with RSSI-based methods, the path-loss parameters regarding different gateways have been estimated based on their location, and their estimated distance accuracy increases for higher distances. In addition, it is dependent on the dynamics of the environment. To improve RSSI-based localization, it is essential to provide an optimum environment partitioning and multi-slope path-loss model for different parts. Based on the results, this approach can lead to between 4 and 10 dBm improvements in estimated path-loss accuracy that leads to distance estimation improvement between 100 and 300 m. On average, this provides 50% improvement in distance estimation accuracy. In addition, a dynamic scene analysis for low and high distances can improve the estimated path-loss model. Future work will focus on improving the LoRaWAN positioning accuracy in the harbor by considering a sequential model of continuously measured RSSI data, to improve the estimated location accuracy.

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