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LETTER

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Experimental data set analysis of RSSI-based indoor and outdoor localization in LoRa networks

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Positioning capability represents one of the basic features of modern Internet of Things (IoT) applications. Although this objective may be pursued by using Global Navigation Satellite Systems, cheaper and simpler techniques are more suitable for low-power networks. In this letter, we present a complete experimental data set of received signal strength indicator (RSSI) measurements collected in different indoor and outdoor environments using LoRa radios. Moreover, we apply simple and power efficient localization algorithms on the obtained data set. The main goal of this work is to share both the experimental data set and the preliminary results on localization among the community.

KEYWORDS

IoT, LoRa network, radio localization, RSSI

1 | INTRODUCTION

In the last few years, Internet of Things (IoT) has been growing in multiple applications, such as home automation, smart metering, waste management, and road traffic monitoring. Such examples, besides indoor environments, include outdoor scenarios for which new long range and low-power radio technologies have been developed to enable city-scale networks.

Among the different systems for communications in low power wide area networks (WANs), LoRa is gaining attention[1]. LoRa is a patented technology based on chirp spread spectrum (CSS) modulation, which is able to achieve long distances with limited energy consumption[2]. These features allow transmissions up to kilometers and prolong the battery life to years[3].

Localization is fundamental for IoT applications, where, for example, the measurements from different nodes in traffic monitoring may be useful only if the exact position of each of them is known. An external positioning device, such as global positioning system (GPS), may not be a viable solution due to the high cost and power consumption, especially in IoT networks characterized by a large number of objects. Moreover, GPS cannot be used in indoor environments.

On the contrary, LoRa-based communication may be exploited both to transmit data and to calculate the current position without the need of an external device. Although LoRa targets outdoor transmissions, it may be also exploited for localization in indoor environments—operating in the sub-GHz band, LoRa achieves high wall penetration and robustness against typical indoor multipath effects[4].

Preliminary experiments have been carried out to show that LoRa technology can be used to develop localization systems[(1,5)], but extensive experimental data sets are still missing. Some works explored LoRa communication for time of arrival (ToA), time difference of arrival (TDOA) or angle of arrival (AoA) based localization solutions[1]. However, AoA-based methods require an array of antennas, while ToA/TDoA techniques rely on precise clocks, and TDoA also needs accurate synchronization among anchors. Although it's generally less reliable compared the above-mentioned approaches, received signal strength indicator (RSSI) represents the less demanding technique in terms of both power consumption and hardware implementation. Until now, only few works have evaluated LoRa properties for RSSI based solutions. Research in LoRa and RSSI for outdoor scenarios has focused mainly on localization algorithms for specific noisy environments[1]. Considering indoor scenarios, LoRa signal has been compared to WiFi and bluetooth low energy (BLE), observing that LoRa is more stable and more robust to varying environments[3]. Moreover, RSSI-based ranging estimation, which is useful as an initial step for localization solutions, has been tested successfully[(5,6)]. A hybrid RSSI-GPS based localization system could provide an acceptable trade-off between accuracy and power consumption[7], although leading to higher production costs.

In this paper, we implement a LoRa based transmission system and collect data measurements to characterize the behavior of the RSSI in both outdoor and indoor environments - the outcome of this measurement campaign is a data set of 25 000 samples, which will be shared freely. We then explore the obtained experimental channel characterization through RSSI to improve three localization methods. Two of the implemented methods, that is, Min-Max and Trilateration[(8,9)], are based on geometric analysis, while another one is a statistical algorithm based on the Maximum Likelihood of the measured values[10].

The structure of the paper is organized as follows. In Section 2, a description of the system and the details of the hardware and software setup are given. In Section 3, we present LoRa experimental channel characterization for different scenarios while, in Section 4, we show a comparison among the above-mentioned RSSI based localization algorithms. Finally, in Section 5, conclusions are drawn and possible future works based on our shared experimental data set are presented.

2 | SYSTEM DESCRIPTION

We consider a LoRa communication system, in which data transmission is used also for localization purpose, with the 2-fold advantage of saving power and enabling indoor tracking by avoiding the usage of an external GPS device. Before detailing the channel model and the localization methods, we outline LoRa communication technology. Finally, we highlight the main features of the hardware platform used during tests on the field.

2.1 | LoRa technology

LoRa technology has been designed specifically for low-data rate wireless communication, aiming at covering long distances while consuming low power[2]—these features makes LoRa well suited to IoT applications. While LoRa defines the physical layer features, LoRaWAN specifies the system architecture and network protocols for LoRa capable devices. In particular, LoRaWAN provides a medium access control (MAC) to allow several LoRa end-devices to communicate with a LoRa gateway through LoRa modulation[11].

The LoRa physical layer is based on a chirp spread spectrum (CSS) modulation, which encodes information through chirps with a linear variation of frequency over time. Since chirp pulses vary linearly, a frequency offset between the transmitter and the receiver may be seen as a timing offset, which may be compensated easily at the decoder. Moreover, such feature makes the modulation robust also to a Doppler effect, processed as a frequency offset.

The main LoRa modulation parameters are bandwidth (BW), spreading factor (SF) and code rate (CR). They affect the modulation bit rate, as well as its robustness to interference and its facility of decoding[11]. In LoRa, $\mathrm{SF} = \log_2 n_{\mathrm{chirps}}$ where n_{chirps} is the number of chirps per symbol and a symbol contains 2^{SF} chirps, that covers the whole band. The chirp rate is equal to the bandwidth BW and the duration of a symbol T_{S} is defined as $T_{\mathrm{S}} = \frac{2^{\mathrm{SF}}}{\mathrm{BW}}$.

Furthermore, LoRa includes a forward error correction code whose code rate CR is set equal to $4/(4+n)$ with $n \in 1, 2, 3, 4$. Since there are SF bits of information in a symbol, the useful bit rate R_{b} is given by $R_{\mathrm{b}} = \mathrm{SF} \cdot \frac{\mathrm{BW}}{2^{\mathrm{SF}}} \cdot \mathrm{CR}$.

2.2 | Channel model

Radio channel characterization in a specific environment is obtained through a relationship between the RSSI value and the distance between two radio devices. Specifically, starting from the Friis transmission equation and converting the power from Watts to dBm, a relation between the received power (RSSI) and the distance can be obtained[12]. Its value, here simplified for 1 m reference distance, is usually expressed as $\mathrm{RSSI} = -(10 \cdot n \cdot \log_{10} d - A)$, where A is the received power in dBm when the distance between the transmitter antenna and receiver is 1 m, and n the loss parameter (or loss exponent) of the specific environment. The distance d is obtained as

$$d = 10^{\left(\frac{A-\mathrm{RSSI}}{10 \cdot n}\right)}. \tag{1}$$

The parameter A is related to the physical properties of the radio device, while the value of n heavily depends on the environment and the operating frequency[13]. Friis equation may be applied only under the ideal free space condition, perfect alignment and polarizations of the antennas, without path-loss and fading effects. Although the model is still valid in real world scenarios, the values of both A and n must be found empirically through measurements as specified in Section 3.

2.3 | RSSI based localization algorithms

We experimentally apply three representative localization algorithms two geometric methods, Min-Max and Trilateration, and a statistical algorithm, Maximum Likelihood, with an increasing computational burdening. Specifically the implementations of the algorithms are the same used in[12], allowing us to compare the indoor performance of LoRa with Zigbee.

Min-Max[8] is a localization algorithm highly used due to its easy implementation. The algorithm estimates the position of the target node by computing a square for each anchor i with the anchor at the center and edges' length equal to $2 \cdot d_i$, where d_i is the estimated distance between the target and the ith anchor. Then, the center of the intersecting area among the squares is the estimated position of the target.

Trilateration[9] is another geometry-based method. Instead of computing squares as in Min-Max, Trilateration intersects circles to estimate the target position. In particular, ranging estimation is used to estimate the distance d_i between the target and the anchor nodes. It is supposed that the radius r_i of each circle is equal to the estimated distance d_i for anchor i and the target is in the center of the overlapping area.

Finally, the statistical Maximum Likelihood (ML) method[10] aims at minimizing the mean square error (MMSE) of the estimated distances d_i between the target and the ith anchor. Since such measurements are affected by noise, ML algorithm estimates the target position by minimizing this error via MMSE estimation according. This algorithm shows good results when a high number of measurements is available by minimizing the error variance. However, often the number of measurements is limited and the results are not satisfactory, for example when considering only three anchor nodes[8].

2.4 | Hardware setup

For the tests on the field, we used Libelium Waspmote boards interfaced with a Semtech-based LoRa radio module[14]. Waspmote is a battery-powered hardware platform based on an 1281 Atmel ATmega microcontroller, featuring 128 Kb flash memory, a 4 Kb eeprom, a 8 Kb SRAM and an optional SD card slot. The platform provides also a real time clock that allows to put the platform in sleep mode and wake up periodically, thus increasing battery life.

The LoRa module mounted onto the board is based on the Semtech SX1272 chipset and operates in the 868 MHz ISM band. The module is characterized by high sensitivity: tests run by Libelium showed that is able to cover up 22 Km in LOS scenario and 2 km in urban NLOS with a transmission power of 14 dBm. Our setup uses a transmission power of 0 dBm and rubber duck half-wave antennas for each node.

The programming library implements a simple link protocol created by Libelium, and provides 10 operating modes with predefined LoRa settings for BW, CR and SF. These modes range from the most robust mode 1—slower but able to cover larger distances—to mode 10, which have the highest data rate but less range. Specifically, mode 1 features BW = 125 KHz, CR = 4/5, and SF = 12; on the other side, mode 10 has BW = 500 KHz, CR = 4/5, and SF = 7. As a result, the first mode has a sensitivity of −134 dBm and a maximum data rate of 23 bps, while these values for mode 10 are −114 dBm and 537 bps, respectively. Mode 5 is a trade-off among these two operating modes. A complete description of the configuration values associated to all the available modes is provided in[14]. As explained in Section 4, in an outdoor environment such modes give different localization errors, while in indoor scenario they show similar performance.

3 | EXPERIMENTAL LORA CHANNEL CHARACTERIZATION

According to the channel model described in Section 2.2, we obtain A and n for our LoRa hardware setup and environment by collecting 100 RSSI values between a transmitter and a receiver at different distances. After the data collection phase, we perform a logarithmic interpolation of the average RSSI data according to (1). The resulting fitting curve provides the corresponding values of A and n.

3.1 | Reference environments

For indoor channel modeling, we choose a corridor 37 m long with several rooms on a side to have both LOS and NLOS configuration. For LOS setup, both the transmitter and the receiver are placed along the corridor, while for NLOS configuration the transmitter is located in a room on the side of the corridor without changing the position of the receiver. We move the devices from 5 to 35 m far from each other with steps of 5 m and we acquire 100 RSSI values for each of the 10 available LoRa modes.

To characterize LoRa channel in outdoor environment, we perform the RSSI measurements in a street, with the nodes at a height of 2 m. The street is 330 m long and, as for the indoor scenario, we fix the position of the receiver and move the transmitter—the distance between the two devices varies from 20 to 330 m with a step of 20 m. For each distance, 100 RSSI

TABLE 1 LoRa channel characterization: A and n values for different LoRa modes

	Mode 1		Mode 5		Mode 10	
	A	*n*	*A*	*n*	*A*	*n*
LOS indoor (1-35 m)	−43.0	2.2	−41.0	1.9	−33.7	2.1
NLOS indoor (1-35 m)	−45.3	3.1	−31.8	3.9	−26.1	4.2
LOS outdoor (30-300 m)	−38.3	2.1	−35.6	2.1	−26.4	2.4
Combined LOS in and outdoor (1-300 m)	−45.2	1.8	−41.6	1.8	−34.0	2.0

measurements have been collected for modes 1, 5, and 10. For this outdoor scenario, we perform the RSSI channel characterization only in a LOS configuration. Although the outcome is a model valid for a limited number of outdoor configurations, it could be extended, in the future, towards the loss effects of urban obstacles and the statistical channel variations of a realistic outdoor NLOS environment.

For all configurations, we gathered the raw RSSI values, then we computed the average for a set of 100 samples and, finally, we fed the mean values to the algorithms described below. The original data, the details and the plans of the considered scenarios can be found inside the data set.

3.2 | Channel characterization

Table 1 compares the RSSI behavior in both indoor and outdoor environment: distances from 0 to 30 m refer to indoor scenario, while from 30 to 330 m to outdoor setup. The "combined" option consider indoor and outdoor values as a single set of measurements. The values for A and n obtained from the fitting curves are the key parameters of our LoRa channel characterization. These values change a lot depending on the mode—this is due to the different levels of robustness and sensibility of the LoRa modes.

Preliminary results show that RSSI has a coherent behavior when passing from indoor to outdoor LOS: the strength indicator for larger indoor distances is close to RSSI values for outdoor short distances (Figure 1). Hence, this technology may be used also for indoor communication even though it has been designed for long range communication. Moreover, due to its exponential nature, the RSSI curve shows a floor for higher distances. This behavior would results in poor LoRa localization performance for significant distances between the anchors and the target.

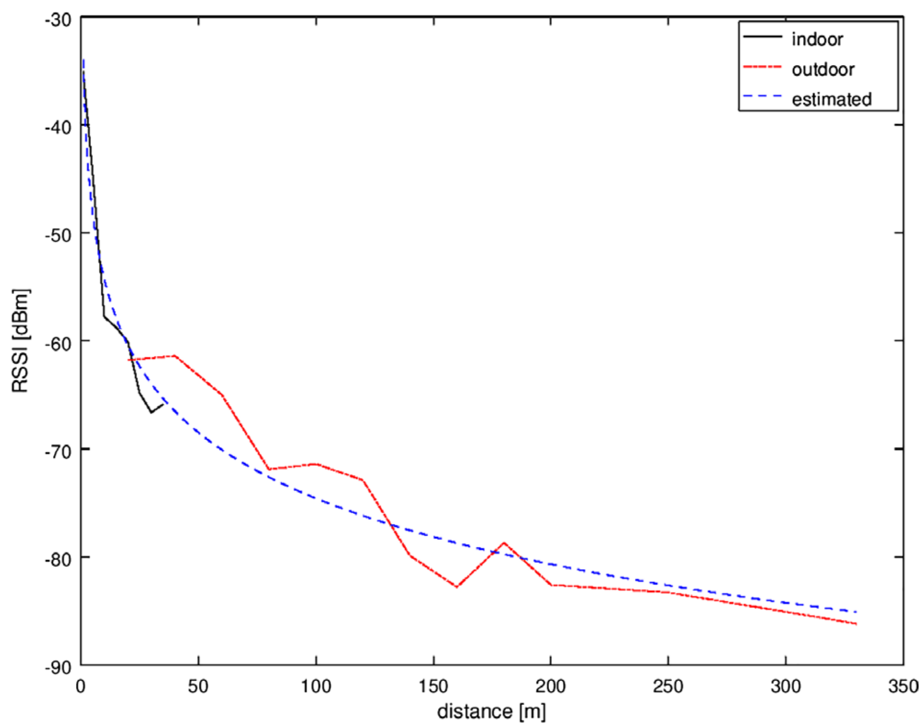

FIGURE 1 Combined indoor and outdoor RSSI in LOS condition

TABLE 2 Minimum/average localization error (in m) with different setups using three anchors at a time

	Trilateration			Min-Max			LS		
	1	5	10	1	5	10	1	5	10
Indoor	0.4/5.5	0.3/5.9	0.3/6.1	0.4/4.9	1.0/4.8	2.1/5.0	0.6/28.0	0.15/44.2	0.7/43.8
Outdoor	8/111	9/117	9/137	10/106	13/113	15/145	26/351	34/385	13/424

4 | EXPERIMENTAL LOCALIZATION

We evaluate the experimental RSSI-based localization solution in two configuration settings, that is, indoor and outdoor. In both environments, the positions of the target node and of the 11 anchors provide both LOS and NLOS links. For each anchor we collect 100 RSSI measurements for each LoRa mode configuration. Then, the values of A and n, previously obtained in the corresponding configuration, are used to estimate the distance from the average RSSI value. Finally, all possible combinations of three anchor nodes and the estimated distances are fed to the Trilateration, Min-Max, and ML localization algorithms.

4.1 | Indoor localization

For the indoor scenario, we consider a 11×7 m wide, first-floor apartment with three rooms and 10-cm-thick walls. Table 2 sums up the average errors in estimating the target position. The Trilateration method achieves the minimum error equal to 15 cm, and all LoRa modes show similar performances: the best combination of anchors provides accuracy in the range of tens of centimeters. This can be considered a satisfactory result for an RSSI-based localization system: similar values can be achieved using the short-range IEEE 802.15.4 standard[12]. On the other hand, the average error of about 5 m is quite high for a 77 m^2 floor. However, fluctuations in the strength of the received signal due to obstacles and walls can results in significant fluctuations in the estimation of the distance. Hence, both the choice of the anchors and the stability of the signal are crucial for achieving high accuracy in an indoor environment.

4.2 | Outdoor localization

The outdoor environment is an urban area of about 0.5 km^2 located in San Giorgio Bigarello, Italy. The position of the nodes is fixed: 6 anchors are in LOS with respect to the target, while the remaining 5 links are in NLOS due to building blocks.

Results shown in Table 2 confirm that Trilateration method performs better than ML and Min-Max, although the latter one is easier to implement and less computationally expensive. Differently from the indoor environment, in this scenario the performance depends on the selected LoRa mode. Indeed, in indoor configurations the short distances map to the steep part of the logarithmic RSSI curve, which turns out more precise localization. On the contrary, in outdoor scenarios, the larger distances correspond to the flat region of the logarithmic RSSI curve, where it is more difficult to estimate the exact distance. Thus, a more robust LoRa mode may help to increase the accuracy—as expected, LoRa mode 1 shows the minimum error in our tests.

Looking at the big picture, the reliability of the localization is not satisfactory in such scenario. The choice of the localization algorithm, the position of the anchors, the stability of the signal, the robustness of the transmitting mode, and the accuracy of the channel model are all crucial aspects—inaccuracies in one or more of these factors can result in an error of hundreds of meters in an urban neighborhood.

5 | CONCLUSIONS

In this letter, we presented a complete experimental data set of RSSI measurements collected in different indoor and outdoor environments using LoRa radios operating in the 868 MHz ISM band. The first round of tests involved a measurement campaign in an indoor and an outdoor scenario. The outcome of this step is a set of A and n values, characterizing the propagation of LoRa radio signal in different environments and configurations. Then, we moved to different, more complex scenarios and we measured the RSSI received by a fixed target from multiple anchors. Using the experimental channel model and the RSSI values, we computed the distances among the nodes and we applied simple and power efficient localization algorithms to estimate the position of the target.

Preliminary results show that LoRa is extremely accurate in some configurations, although is quite unreliable in general—the average error was about a hundred of meters in an urban environment. Ongoing works are devoted to improve RSSI ranging accuracy by exploiting the diversity effect. In more details, distance estimations for a position could be improved by mixing in a suitable manner the values obtained from different LoRa transmitting modes.

While we conducted preliminary experimental tests, the use of LoRa's RSSI for localization still needs to be deeply investigated. To this purpose, we share freely and under a permissive license the obtained data to the community for further analysis.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of the article.

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