LoRa Positioning in Verification of Location Data's Credibility

Anna Strzoda, Rafał Marjasz, and Krzysztof Grochla

***Abstract*—The LoRa is a novel radio communication technology providing low power and a high range of data transmission. The LoRa transmission may be used for a low-cost localization to estimate the network nodes' location. Some recent research showed that the location could be found with reasonable accuracy, with median error as low as tens of meters. Still, such results are achieved in a controlled environment with low interferences. We first evaluate the LoRa localization using an extensive data set of a telemetric network of a few thousand devices. We show that although the direct positioning based on trilateration provides limited accuracy, the measurement of LoRa transmission may be successfully used to evaluate the credibility of location information. The information about which gateways received the data and the RSSI measurements allow us to verify if the potential coordinates of a location are accurate. We propose a metric for location verification and estimate its credibility on a sample of measurements from the LoRa telemetry network.**

***Index Terms*—LoRa, positioning, trilateration, multilateration**

I. INTRODUCTION

The Low Power Wide Area Networks (LP WAN) provide a high range of wireless communication, with distances up to a few tens of kilometres. Although the data rate is low, the device's low cost and energy utilization have allowed the LP WANs to attract many potential users. Few radio technologies are realizing the LP WAN concept, such as MIoTy, LoRa and Sigfox. Those technologies enable battery-powered devices to communicate over a long period using a single battery and have found multiple applications in telemetry, Smart City and remote control. The most commonly used LP WAN radio technology is LoRa. The LoRaWAN standard [1] defines the packet format and the message exchange sequence between end nodes and gateways. The LoRaWAN uses a star-of-stars topology, where multiple gateways receive messages transmitted by the end devices. The signal strength measurements received by the multiple gateways may be used to estimate the device location. The LP WANs are often used for use cases in which nodes are stationary (e.g. telemetry or lamp post control), so the measurements may be averaged over a long period to increase the accuracy. But the variability of a signal is significant due to the use of unlicensed spectrum and interferences of other transmissions using the same frequencies. Additionally, the multipath propagation and the signal deflection make the received signal level imprecise. It may change rapidly, e.g. the spatial location of objects between the node and the gateway. Some factors also influence the signal propagation over more extended periods, e.g. the presence of leaves on the trees.

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Some recent research proved that LoRa and LoRaWAN communication may be used to estimate the transmitting devices' location. The true-range multilateration allows us to find the location of the signal source using the estimation of distances between the LoRa node and multiple gateways, being spatially-separated known locations. A few papers reported that the location could be found with good accuracy, with average error as low as tens of meters [2]–[4]. However, in many cases, it is evaluated in very optimistic transmission conditions, e.g. using line-of-sight communication and on a small data set. Very little research shows the accuracy of LoRa positioning in real life, with a large data set and placement of devices, including both indoor and outdoor nodes.

In many network deployments, a device's most probable location is known and denoted during the network deployment. In most telemetry networks, the technician denotes the coordinates at which the device is placed. In other use cases, such as e.g. smart metering, the nodes' location may is known from the address of the property in which the meter is installed. Such location information is, however, unreliable, as the technicians make errors when noting the location, devices are sometimes relocated, or the address may point to another owner's residence. Thus, the probable location information validation is also a valid problem and may be helpful for the network operator, e.g. to detect the errors within the location database or to detect whenever a device has been relocated. It has been referred to in the literature as a Location Verification System [5], [6], which verifies whether the location information provided by a device is credible or not.

This paper discusses whether the LoRa positioning accuracy allows us to pinpoint a device to specific coordinates directly or if it can be used to validate potential location data. We show an analysis of the true-range multilateration accuracy in realistic conditions when little is known about the radio link's attenuation and the node's placement. Based on a data set covering a city-wide telemetry network of more than 4 000 devices, we discuss the average error in distance and location estimation. Next, we propose a method for validation if a potential location is credible, and we evaluate this method using subsets of the above data.

The rest of the work is organized as follows: in the following section, we present a review of the LoRa position literature. The third section describes the dataset used. In the fourth section, we discuss the problem of verification of the potential location credibility and propose an algorithm. In the following section, we evaluate the proposed algorithm using data from real transmission. We finish with conclusions in the sixth section.

II. LITERATURE REVIEW

The positioning in wireless networks is a widely researched topic. Although many of the wireless devices are equipped with a Global Positioning System (GPS) interface, the use of GPS increases the cost of device and uses additional energy. Therefore, the possibility of using low-power-wide-area signals for outdoor positioning is still needed, especially in low cost networks which do not require high accuracy or in indoor devices. The most commonly used positioning methods using LoRA signals are based on RSSI and path-loss-model, time of arrival (ToA), time difference of arrival (TDoA), and the fingerprint technique.

Semtech has implemented a proprietary geolocation functionality in LoRaWAN based on TDoA. The LoRa Alliance claims this solution achieves a positioning accuracy of 20 m to 200 m [7], depending on conditions. A positioning method based on TDoA is also used in [8] with a median location error below 500 m. The algorithm is evaluated on measurements collected during driving, cycling or walking in public with a mobile node. The same dataset has been used to evaluate the positioning proposals described in [9]. The authors compare the accuracy of TDoA-based and RSS-based (Received Signal Strength) localization in the LoRa network. A more pessimistic median error has been obtained for the RSS method - about 1 km, whereas, for TDoA, it is almost ten times smaller.

The combination of TDoA and AoA localisation in LoRaWAN is presented in [10] assuming LoS and NLoS scenarios. The most optimistic mean position error is around 160 m. In [11], the authors describe the LoRa localisation system using a multilateration algorithm based on TDoA. Experimental results give a positioning accuracy of around 0.1 km in a 6 km^2 urban area. But, the testbed is relatively poor and consists of one end node and four LoRa gateways. In [2], the authors propose algorithms to improve localization performance in noisy outdoor environments based on the path loss model and estimated RSSI error. Experimental results give an error from several to several dozen meters over the distance between devices of about 100 m. Similar results are obtained in [3]. The authors also present the RSSI-based localization techniques to reduce the effect of noise in LoRa networks for outdoor and indoor environments. The use of LoRa in outdoor and indoor positioning is also considered in [12]. The authors apply Wiener filters to reduce noise in RSSI measurements and use a trilateration algorithm. The most optimistic mean location error is less than 0.5 km in an urban area of 0.5 km^2, and 20-30 m for the indoor environment. The proposed method has been evaluated on the available dataset [13].

A LoRaWAN and Sigfox location datasets are presented in [14] as a material for evaluating fingerprint algorithms in large outdoor environments. Measurements were collected using mobile nodes (mounted on postal cars) moving around in the urban area of 50 km^2, which is a bit larger than in our dataset. The authors declare a mean location error of around 0.4 km achieved by the kNN-based fingerprint technique on the LoRaWAN dataset. Moreover, this collection has been also used to evaluate [4] or a fingerprinting and machine learning system-based architectures presented in [15], [16]. The most optimistic mean location error is below 200 m.

In [17], the authors propose the positioning system using the fingerprinting technique based on hi-res satellite images from the Deep Globe dataset [18]. In particular, the algorithm identifies the land-cover type using pixels classification and, depending on it, adjusts the path loss exponent to improve positioning. The median estimation error is below 50 m. Another locating proposal [19] is based on RSSI-interpolated fingerprint maps obtained from the propriety outdoor testbed deployed on an area several hundred times smaller than ours.

A few research papers have considered the problem of verifying location accuracy based on a wireless network signal. A. Tahbaz-Salehi and A. Jadbabaie in [20] present three distributed algorithms for coverage verification in sensor networks with no location information. Still, the paper only focuses on the localizing coverage holes problem and considers distributed sensor network topology. Some works use LoRa, e.g. [21], [22], which uses GPS to measure the location, not LoRa positioning. The paper [5] describes an information theory framework based on the threshold used in detecting a spoofed location.

Most of the mentioned papers include real deployment case studies. However, no works consider such a comprehensive, commercially used and real-life network topology as we do. Only one evaluation dataset includes a more significant number of LoRa gateways than ours. And a slightly greater testbed-deployment area. Nevertheless, the large-scale effect is achieved with vehicle-mounted mobile nodes rather than a regular network infrastructure.

III. DATASET

This section describes the comprehensive large-scale LoRa dataset considered in our research. We have used the data collection from our previous study [23]. The measurements are collected from the commercially-used network infrastructure deployed around 40 km^2 in one of the typical Polish cities. This network topology includes urban and suburban areas with different densities of node distribution in space. The network consists of over 6000 end devices and 16 LoRa gateways. The devices were transmitting two packets per day to LoRa gateways. The collection includes approximately 4 mln data points collected over seven months. The single data point provides information about RSSI and SNR measures, an id number of the LoRa gateway that received the radio packet and reception time.

The exploration of the dataset is twofold. First, estimate the RSSI-distance curve coefficients described in section IV-A and evaluate the localisation method. The measurements used for the positioning method evaluation are not included in the curve fitting process to provide valuable results. The evaluation process considers 400 end nodes with exact inevitable coordinates and at least 30 radio packages provided to each of at least three LoRa gateway.

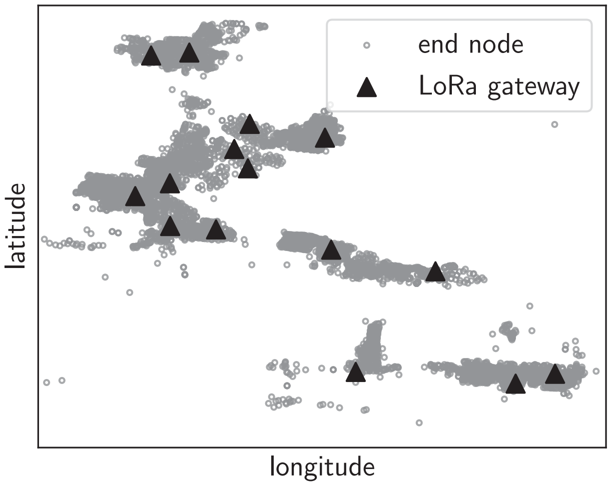

Fig. 1. The real-life LoRa network infrastructure deployed in a Polish city.

IV. Methodology

Techniques based on the signal level are commonly used for LoRa localization due to the availability of RSSI measurements in LoRa interfaces. The location is calculated using trilateration (true range lateration) which can be formulated as an optimization problem and solved by non-linear least-squares methods. An optimization method, e.g. Levenberg-Marquardt [24] may be used to find a location with the lowest square error. The trilateration algorithm requires at least three distance values between a search point (a point whose position is unknown) and nodes with known coordinates. However, this method assumes a strong correlation between the estimated distance and the actual distance in the field. Below we show the evaluation of how distance values are provided by a constructed function that maps RSSI values into the distance map to a distance measured on the ground.

A. Distance function

The estimated distance is expressed as an exponential function of the RSSI measure.

$$d(\overline{RSSI}_{ij}) = 10^{\frac{\overline{RSSI}_{ij}-a}{b}}, \qquad (1)$$

where $\overline{RSSI}_{ij}$ is a mean value calculated from all RSSI measurements obtained in the communication between i_{th} end node and j_{th} LoRa gateway. The parameters of the function: $a = -119.3$ and $b = -8.7$ are fitted curve coefficients fitted by the least-squares method. Figure 2 illustrates the logarithmic function that best fits a series of distance vs RSSI data points. Each point of the data series corresponds to an average RSSI value calculated from packets delivered from one end node to a given LoRa gateway. The parameters a and b determined in the fitted curve (fig. 2) were obtained for deployment with specific parameter values such as antenna gain or transmission power. In the case of applying this solution in different deployments, the path loss should be determined, considering the parameter values specific to given appliances, or a path loss estimation typical for a LoRa networks may be used, which has been estimated in a few research papers, e.g. in [23], [25]. These calculations should be considered to determine new parameters a and b, specific to the network implementation.

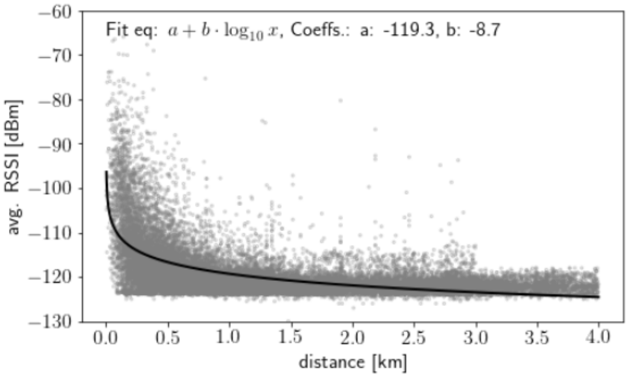

Fig. 2. The fitted logarithmic curve of the relationship between the distance and its average RSSI.

V. Comparison between estimated and real distance

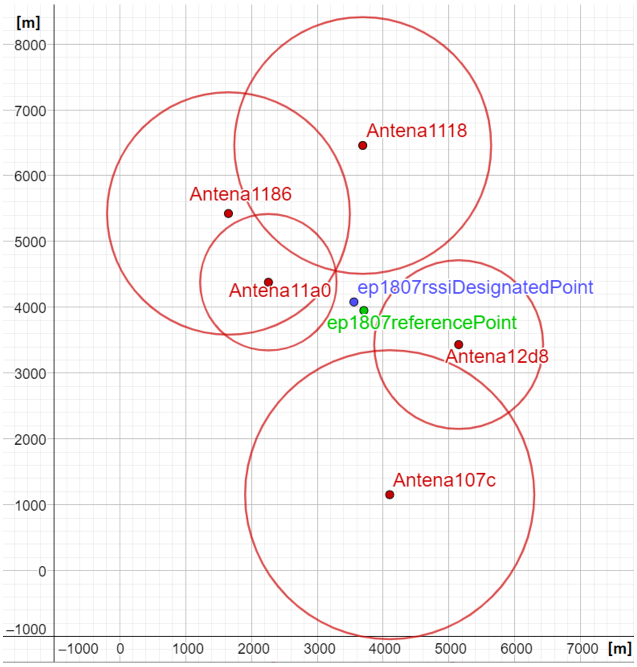

Fig. 3. Visualisation of selected single end node localisation using the proposed method. The blue point represents the localisation as an outcome of RSSI analyse based trilateration. The green point is the reference localisation taken from the GPS database. The red circles reflect the distances from the appropriate antennas resulting from the fitted RSSI vs distance curve. The error difference in distance between points equals 208.83 meters.

A particular case shown in 3 visualizes the outcome of the distance estimation for a sample end. The visible red circles represent the calculated distances from appropriate gateways receiving no less than the assumed number of packets. From these distances, the trilateration algorithm has calculated the position marked with a blue point. The green point marks the reference location taken from a database, and the calculated error between both positions is 208.83 meters. We can see no single location where the circles showing the estimated distances meet, and the inaccuracy is significant due to the mismatching of the distances to different gateways.

The LoRa transmissions are characterized by high variability of received radio signal strength, which has been shown, e.g. [26] or in our previous work [23]. Additionally, according to [27], there are significant channel gain variations over different LoRa channels. Although the influence of this variability may be partially minimized using advanced filtering, it is unlikely that the distance estimation based on the signal level in LoRa is accurate, leading to even higher location accuracy errors.

A. Correlation between measured RSSI and the distance

Having a data set containing the actual positions of end nodes and data points with RSSI measure information received by the LoRa gateways, we attempted to verify each end node's actual position using the collected RSSI data. For each end node whose position needs to be verified, the population of RSSI measurements is considered in the communication between a given end node and each LoRa gateway. RSSI values recorded for received radio packets are calculated into distances according to the formula 1. We aim to provide a measure based on an obtained distribution of distances between the end node and the LoRa gateway.

The position verification process calculates the distance between a given end node and each LoRa gateway within range and determines the distance-based measures for included gateways. The accurate coordinates of the LoRa gateway are known. Then, the value of the cumulative distribution function at the obtained distance is determined for each LoRa gateway within range. Finally, the determined values per each gateway are used to derive measures from the formula 2.

In order to make distance comparisons, the following dependency measure was developed:

$$Rssi(d_i) = 1 - 2 \times |F(d_i) - 0.5|, \tag{2}$$

where

- d_i – is the distance in [km] between the real end node position and the i-th LoRa gateway position within the radio range of the end node,
- $F(d_i)$ – is the cumulative distribution value of the distance distribution determined from the RSSI data in the communication between the end node and the LoRa gateway.

The constructed measure rewards distances d_i having values equal to or close to the distance being the median of the distance distribution determined based on RSSI data. The values of the thus constructed measure belong to the interval $[0, 1]$. Depending on the number of LoRa gateways recording the radio signal from the end point, we get the vector $\overrightarrow{Rssi} = [Rssi(d_{i_1}), \cdots, Rssi(d_{i_n})]$ having from $n = 1$ to a maximum of $n = 16$ values calculated individually for each LoRa gateway within the radio range of the end point. For obtained vectors, we define a consistent measure $\overrightarrow{Rssi}_{(kp)}$ independent of their size, where (kp) is the k-th percentile of the vector $\overrightarrow{Rssi}$. The value represented by the hundredth percentile is the best result achieved by one of the LoRa gateways. Figure 4 presents the distribution of the value of the dependency measure $\overrightarrow{Rssi}_{(100)}$.

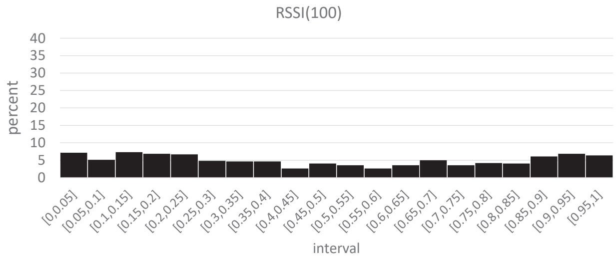

Fig. 4. The distribution of values achieved by $\overrightarrow{Rssi}_{(100)}$ measure.

The plot in fig. 4 shows the minimal dependency between the measured average RSSI and the distance. The distribution is almost uniform, and as a result, there is no clear correlation that can be derived, and the use of RSSI to validate if the distance between the node and the gateway is correct is not conclusive.

VI. PROPRIETARY METHOD OF LOCATION VERIFICATION

We developed a method for verifying the reliability of the end node location based on the proposed measure M_v that calculates one consistent numerical value characterizing the end node based on its set of features. Considerations for the measure were based on identifying irregular distances between LoRa gateways receiving the signal from the end nodes. If the end node location is accurate, then the end node signal should be received by access points in its immediate vicinity with the appropriate frequency (number of received packets). The following measure was developed based on the information about packet transmission in the LoRa network:

$$M_v = 1 - \sum_{i=1}^{N} f_{0-1}\left(\frac{diff_i}{Grdn}\right) \times \frac{Counts_i}{Soc}, \tag{3}$$

where

- $f_{0-1}(x) := \begin{cases} x, & \text{for } x \in [0, 1) \\ 1, & \text{for } x \geq 1 \end{cases}$
- $diff_i$ – denotes the difference in the positions of the array cells between the two ways of sorting the array:
  - in ascending order of the distance between the end node and the location of the i-th LoRa gateway;
  - in ascending order of the number of packets delivered to the i-th LoRa gateway.
- N – number of gateways
- $Grdn$ – (Gateways Receiving Data from Node) number of LoRa gateways recording packets received from the end node,
- $Counts_i$ – number of packets received by the i-th LoRa gateway,

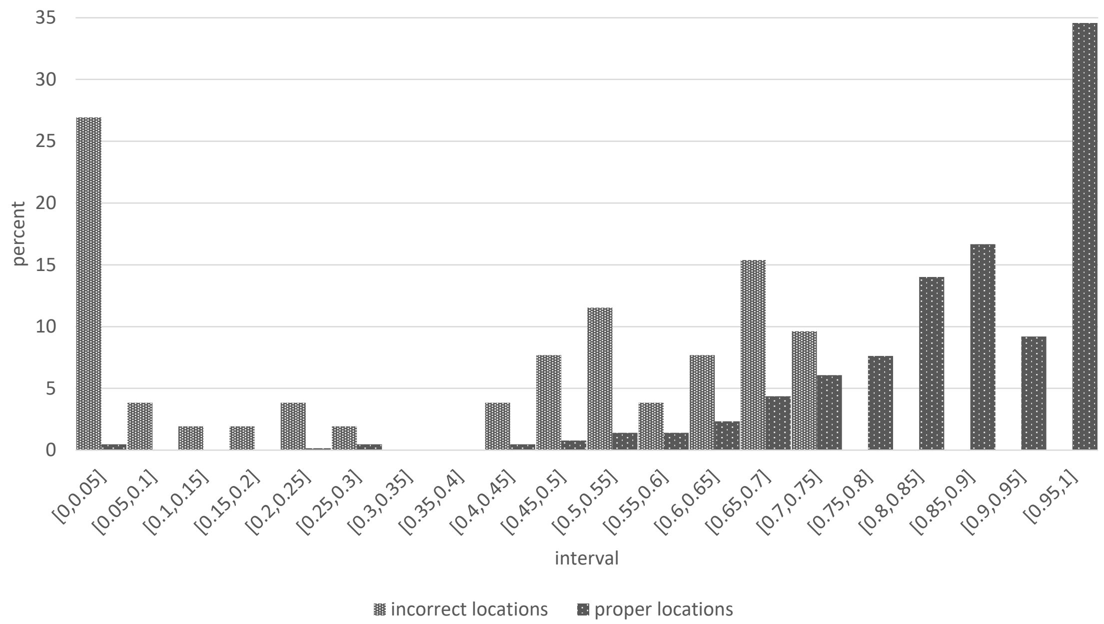

Fig. 5. The distribution of values achieved by M_v measure. The "proper locations" set stands for accurate and verified coordinates, while the "incorrect locations" set contains coordinates verified to be incorrect entries in the available LoRa dataset.

- Soc – (Sum Of Counts) the total number of packets received by the LoRa gateway.

The values of this measure belong to the interval $[0, 1]$. Figure 5 presents the measure distribution of values calculated for two sets of locations. The "proper locations" set contains end nodes with verified location coordinates. The "incorrect locations" set contains unique 52 end nodes coordinates verified as incorrect entries in the available LoRa dataset.

The proposed measure reaches high values for locations considered to be accurate. A M_v metric value higher than 0.8 indicates the correctness of the coordinates correlated with the measure. On the other side of the scale, we can observe that M_v values being close to zero indicates that it is almost certain that the node coordinates are not correct. The intermediate values within the interval $[0.2; 0.8]$ include cases for both sets of end node locations; thus, we cannot determine whether the coordinates are accurate or faulty.

The proposed metric is based on the correlation between the packet delivery to different gateways and the location. While it is highly unlikely that a distant location served by other gateways has a similar value of the proposed metrics, it may happen that some obstacles may increase the attenuation and slightly reorder the gateways. This leads to the metric values in the middle of the scale, showing some uncertainty. But the comparison between the plots shown in figures 6 and 4 shows that the proposed metric can be useful to indicate the location credibility.

VII. CONCLUSIONS

This paper discusses the applicability of LoRa positioning in a real-life, large-scale telemetry network. We first evaluate the LoRa localization using an extensive data set of a telemetric network of a few thousand devices. Our analysis shows little correlation between the distance from the gateway to the end node estimated using RSSI and the real distance measured in the field. We show that although the direct positioning based on trilateration provides limited accuracy, the measurement of LoRa transmission may be successfully used to evaluate the credibility of location information. The information about which gateways received the data and the RSSI measurements allow us to verify if potential coordinates of a location are accurate and create a LoRa location verification system.

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