A Wiener-based RSSI localization algorithm exploiting modulation diversity in LoRa networks

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***Abstract*—Modern wireless sensor networks (WSNs) for Internet of Things (IoT) applications require low-complexity algorithms for positioning, due to the large number of nodes with low power consumption. Thus, simple received signal strength indicator (RSSI) based ranging techniques represent an attractive option for low power systems such as LoRa ones. However, interactions of the RSSI with a real-world environment are difficult to predict and often lead to significant errors in the localization process. Based on this, a novel algorithm is proposed to improve the RSSI ranging output by a Wiener-based method. According to the free-space path loss model, the distance is expressed as an exponential function of the collected RSSI measures, considering, during the training and calibration phase, the channel model information, i.e., the received power at 1 m and the loss exponent. The presented algorithm minimizes the distance logarithm error, instead of interpolating the free-space path loss model as in common solutions, resulting in a more precise ranging and positioning. Moreover, we also study the possibility to suitably combine the diversity information coming from the LoRa physical layer modes, corresponding to different data rates and bandwidths. The performance of the proposed algorithm is evaluated by using both simulated and real experimental data sets, proving the effectiveness of the presented solution compared to existing RSSI-based methods.**

***Index Terms*—Radio Localization, RSSI, IoT, LoRa network, Wiener filter.**

I. INTRODUCTION

LOCALIZATION is fundamental for many IoT applications where, for instance, sensed measurements shall be paired with device positions [1]. While Global Positioning System (GPS) is the default solution to most localization problems, for the case of IoT, external GPS devices may not represent a viable solution due to the high cost and power consumption. Furthermore, it cannot be used in most indoor environments. In all these cases, the current position may be computed exploiting the ongoing communication itself without the need for an external device.

Long Range (LoRa) is an emerging technology, suitable for the Internet of Things (IoT) market, since it targets low-power wide-area (LPWA) networks of wirelessly-connected and battery-powered nodes, operating in the Industrial, Scientific and Medical (ISM) bands.

The LoRa physical layer has been designed for outdoor transmissions and is able to cover a range of 3050 km, however distances of about 35 km are more common in rural areas. It is based on a chirp spread spectrum modulation (CSS) [2], which allows long distance communications with a limited power consumption, prolonging the battery life to years [3], [4].

However, since it operates in the sub-GHz band, the same technology can be also exploited in dense urban and indoor environments due to its high penetration and robustness to noise and multipath fading effects [4]–[6].

The peculiar long-range and low-power features of LoRa makes it an interesting candidate for both outdoor and indoor IoT applications, even to support localization. On the one hand, it may be profitably used for positioning in outdoor environments in industrial applications and smart environment, such as smart metering and environment monitoring. On the other hand, its penetration capability allows to exploit LoRa for indoor localization. Indeed, while recent solutions for positioning in large facilities, such as warehouses and multistores, require the installation of several access points due to the short range of the common WiFi and Bluetooth Low Energy (BLE) based RF signals, the LoRa long range feature would allow the deployment of a lower number of nodes or access points to achieve comparable operations.

Preliminary experiments have been already carried out to show that LoRa technology can be used to develop localization systems, exploring LoRa communication for Time of arrival (ToA), Time Difference of Arrival (TDOA) or Angle of Arrival (AoA) based localization solutions [2]–[5]. Nonetheless, these methods require either additional hardware on the antenna side (AoA) or highly precise (ToA) and synchronized (TDoA) clocks. Conversely, Received Signal Strength Indicator (RSSI) values can be obtained without additional hardware, thus representing the less complex and energy-hungry ranging approach.

RSSI ranging is negatively affected by unknown propagation environments. As such, localization algorithms which exploit channel state information definitely provide better performance at the expenses of a significant greater complexity. While they are used to improve accuracy in WiFi Networks [7], the complexity issue and related energy consumption prevents their implementation in simple LoRa devices. By improving ranging, our aim is to provide an effective way to improve localization results from any localization algorithm.

In [2], RSSI based localization algorithms have been evaluated for LoRa outdoor scenarios in noisy environment, while in [4], a RSSI based ranging estimation has been proposed for LoRa indoor applications. Preliminary results in [8] have shown how RSSI-based ranging with LoRa provides accept-

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able results in an indoor environment; on the other side, localization in an urban neighborhood scenario resulted in errors up to hundreds of meters. Suitable methods are thus required to improve the performance of RSSI-based localization solutions for LoRa systems.

Filtering techniques (e.g. Particle, Bayesian, and Kalman) are usually applied to the localization process [9]–[11] to filter out noisy measurements and improve accuracy.

In this paper we derive a new method to improve RSSI ranging accuracy by solving a Wiener-Hopf equation which minimizes the distance logarithm derived from the Friis path loss model equation. Further, we formulate the distance logarithm as a linear combination of RSSI measurements coming from different LoRa physical layer transmission configurations, or modes, obtained by varying the modulation parameters. In this sense, the solution of the Wiener-Hopf equations represents the weights of such combination, used for deriving distance and positioning. Note that the proposed algorithm represents a valid alternative to the commonly employed interpolation methods [12], [13].

In order to better characterize the proposed algorithm in the statistical sense, the performance of the proposed solution has been evaluated by considering both real experimental data and simulations based on a model whose parameters are derived from the same data set [8], [14], therefore integrating the experimental results with larger simulated data sets.

Simulation results prove the effectiveness of the proposed method, whose complexity may be kept low solving the Wiener-Hopf equation by the stochastic gradient algorithm [15], as specified in Sec. III-B.

The rest of the paper is organized as follows. In Section II, we describe the system model, while the implementation details of the proposed Wiener block filter are described in Section III. In Section IV, we show performance evaluation results of the proposed solution when applied both to simulated and publicly-available experimental data. Finally, we conclude and discuss future research plans in Section V.

II. System Description

LoRa communication systems have been specifically designed to cover long distances at low data rates with low power consumption [3], making this technology particularly well suited to IoT applications. In more details, LoRa defines the physical layer parameters based on a chirp spread spectrum (CSS) modulation, while LoRa wide area network (LoRaWAN) addresses the system architecture and network protocols for LoRa capable devices, providing a medium access control (MAC) to allow several LoRa end-devices to communicate with a LoRa gateway through LoRa modulation [16].

A. LoRa Physical Layer

Since LoRa CSS modulation encodes information through chirps with a linear variation of frequency over time, a frequency offset between the transmitter and the receiver may be seen as a timing error, and compensated easily at the demodulator, making the receiver also robust to Doppler frequency shifts [16].

The modulation diversity may be obtained by changing the following physical layer parameters: the bandwidth B, the spreading factor S and the code rate R_c.

The LoRa standard unconventionally defines the spreading factor as

$$S = \log_2 (N_c) \tag{1}$$

where N_c is the number of chips per symbol.

In LoRa, the chirp rate is equal to the bandwidth B and the duration of a symbol T_S is defined as

$$T_S = \frac{2^S}{B} \tag{2}$$

Furthermore, the LoRa physical layer includes a forward error correction code, whose code rate R_c may be set equal to $4/(4+n)$ with $n \in 1, 2, 3, 4$.

Since a symbol corresponds to S information bits, the useful bit rate R_b is given by

$$R_b = S\frac{B}{2^S}R_c \tag{3}$$

Different spreading factors S and code rates R_c may be set in 10 physical layer modes as reported in Table I. The main idea of this work is to exploit the diversity that may derive from measuring RSSI values at the different transmission modes, used as input for a Wiener filter to improve ranging operation.

TABLE I: Configurations of different LoRa modes

Mode	B (kHz)	R_c	S	Sensitivity (dBm)
1	125	4/5	12	-134
2	250	4/5	12	-131
3	125	4/5	10	-129
4	500	4/5	12	-128
5	250	4/5	10	-126
6	500	4/5	11	-125
7	250	4/5	9	-123
8	500	4/5	9	-120
9	500	4/5	8	-117
10	500	4/5	7	-114

B. Channel Path Loss Model

Radio channel characterization in a specific environment may be obtained from Friis transmission equation, deriving a relationship between the RSSI value, i.e., the received power P, and the distance between two transceivers [8], [17]–[21]:

$$P = -(10n \log_{10} d - A) \tag{4}$$

where A is the received power in dBm when the distance between the transmit and receive antennas is 1 m, and n the path loss exponent of the specific environment.

The distance d may be obtained as

$$d = 10^{\left(\frac{A-P}{10n}\right)} \tag{5}$$

While the parameter A only depends on the physical properties of the transceiver, the path loss exponent n is determined by both the specific propagation environment and the transmitted signal spectrum.

Although Friis equation may be applied only under the ideal free space condition, perfect antenna alignment and polarization, without considering fading effects, the model may be used in real environments where the parameters A and n are empirically determined through measurements [8], [22].

III. RSSI-based Wiener Ranging Algorithm

As reported in [8], equation (4) may be used to find the A and n values for a specific propagation environment, via a logarithmic interpolation performed over a data set collected during the calibration/training phase.

In this work, we propose an alternative method which aims to improve the ranging accuracy by means of a Wiener filter, whose coefficients are computed during the training phase, using the channel characterization described in Section II-B. Moreover, we propose to improve the ranging performance by exploiting the different RSSI values measured for each LoRa mode.

The different LoRa settings may be quickly generated through few code statements during the configuration phase of each node.

A. Wiener Approach Formulation

Solving equation (4) by the distance logarithm

$$\log_{10} \hat{d}(i) = \frac{A}{10n} - \frac{P(i)}{10n} \tag{6}$$

where the index i refers to the i^{th} measurement of the training phase, and $\hat{d}(i)$ represents the estimated ranging distance.

The estimation of the distance logarithm may be improved by a weighted average of the measured RSSI values of each LoRa modes

$$\log_{10} \hat{d}(i) = \sum_{j=1}^{N_m} \left(\frac{A_j}{10n_j} - \frac{P_j(i)}{10n_j} \right) \tag{7}$$

where N_m is the number of used LoRa modes, which is equal to 10 if all the transmission modes are used, and A_j, n_j represent respectively the path loss intercept and exponent for each mode.

Equation (7) can be re-written as

$$\log_{10} \hat{d}(i) = A_0 - \sum_{j=1}^{N_m} w_j P_j(i) \tag{8}$$

where $A_0 = \sum_{j=1}^{N_m} \frac{A_j}{10n_j}$ and $w_j = \frac{1}{10n_j}$.

The vector $\mathbf{w} = [w_1, w_2, ..., w_{N_m}]$ may be viewed as being composed of the coefficients of a Wiener block filter, which can be computed by minimizing the mean square error of the distance logarithm, defined as

$$\epsilon = E\left\{ \left[\log_{10} d(i) - \log_{10} \hat{d}(i) \right]^2 \right\} \tag{9}$$

The error defined in (9) keeps the formulated problem linear with respect to the Wiener coefficients w_j which may be computed by replacing $\log_{10} \hat{d}(i)$ in (9) with (8), and setting the following partial derivatives equal to zero

$$\frac{\partial \epsilon}{\partial w_j} = 0, \text{ for } j = 1, 2, ..., N_m \tag{10}$$

The solution of equations (9), (10) may be obtained by inverting an autocorrelation matrix of size $N_m \times N_m$ or by looking for a stochastic gradient iterative solution.

Since the accuracy of the estimated ranging distance by means of RSSI measures decreases with higher distances, the minimization of the distance logarithm error may be viewed as a sort of non-linearly weighted error computation.

B. Wiener Coefficients Computation

Solving equations (9,10) for the coefficients w_j leads to the following Wiener-Hopf equation

$$\mathbf{w} = \mathbf{R}_P^{-1} \mathbf{r}_{dP} \tag{11}$$

where $\mathbf{R}_P = \{r_P(k)\}$ is the autocorrelation matrix whose elements are $r_P(k = j - l) = E\{P_j(i)P_l(i)\}$, and $\mathbf{r}_{dP} = \{r_{dP}(k)\}$ is the cross-correlation vector whose elements are defined as $r_{dP}(k) = E\{[A_0 - \log_{10} d(i)]P_k(i)\}$, and $j, l = 1, 2, ..., N_m$. Once the coefficients w_j are calculated, the estimated distance $\hat{d}(i)$ may be computed using equation (8).

It is important to underline that when $N_m = 1$, the presented Wiener approach can be reduced to a simple single coefficient solution, which represents a valid alternative to different interpolation methods applied to (5).

In order to limit the computation complexity of the calibration, the coefficients w_j may be computed by the stochastic gradient algorithm [15]

$$\mathbf{w}_{i+1} = \mathbf{w}_i + \mu e(i) \mathbf{P}_i \tag{12}$$

where $e(i) = \log_{10} d(i) - \log_{10} \hat{d}(i)$, μ is a suitable step size, and $\mathbf{P}_i = [P_1(i), P_2(i), \cdots, P_{N_m}(i)]$.

It is important to highlight that the proposed solution has a very low impact, and it can be implemented by using the RSSI values measured by employing the original firmware, while equation (7) and (12) can be easily added to the internal board firmware.

IV. Performance Evaluation

The proposed algorithm performance has been evaluated by using the freely available experimental data set [14] detailed in [8]. As outlined in the following, the experimental data have been also used to define the main parameters of the simulation model, used to better evaluate the algorithm performance in a statistical sense.

The proposed algorithm has been compared with a modified version of a common RSSI method, to exploit anyway

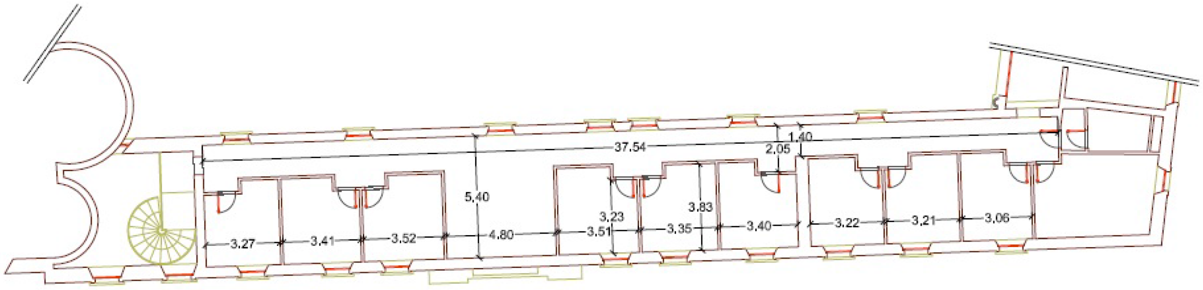

Fig. 1: Plant of the indoor environment used for channel characterization measurements

TABLE II: Average ranging error (in m), indoor experimental dataset

Input data	LI mode 1	Wiener mode 1	LI mode average	Wiener all modes
average RSSI	14	5.3	23.1	15.4
maximum RSSI	4.63	5.5	10.48	6.5
instantaneous RSSI	16.65	5.3	26.47	16.74

Fig. 2: A view of the experimental setup used for channel characterization measurements of the indoor environment

the multi-mode information. Specifically, the modified RSSI algorithm is obtained by averaging the estimated distances for the different modes through the logarithmic fitting of equation (5). As a special case, we also consider when only one single LoRa mode is used in both the proposed and the compared approaches. This corresponds to the mono-dimensional case with only one Wiener coefficient in the presented algorithm, and to a common RSSI method [21] for the other solution.

The proposed Wiener-based approach may be seen as an alternative to the use of equation (5), which represents the state-of-the-art (SoA) of RSSI based localization techniques. This is the reason why we also compare the performance of the two algorithms in the mono-dimensional case, without exploiting diversity.

Fig. 3: A view of the experimental setup used for channel characterization measurements of the outdoor environment

A. *Ranging Experimental Results*

We consider the indoor and outdoor scenarios described in [8], testing the proposed algorithm performance by considering 11 anchors with 100 RSSI measurements for each LoRa mode configuration in the data set [14].

For the indoor scenario, the training phase of the algorithm, i.e., equations (11,4), considers the reference data of the indoor channel characterization, based on 100 RSSI values for each LoRa mode, collected at different distances between the transmitter and the receiver, varying from 1 to 35 m, with a step size equal to 5 m (see the environment plant in Fig. 1, and a view of the experimental setup in Fig. 2).

In order to make the obtained results independent on the training phase, we have used different environments for the training and evaluation phases, by considering different but similar propagation conditions. Thus, the two experimental indoor environments, used respectively for channel characterization and experimental results, are different since they have been collected in different buildings.

The outdoor data set has a similar structure, i.e., two distinct environments used for channel characterization and localization results, considering 11 anchors at distances from the target ranging from 68 to 466 m. Since when the distance increases, the configurations (modes) with the higher performance may go out of their sensitivity because the code-rate is too high for the considered distance, we have chosen the modes with acceptable receiver performance at the higher distances. In particular, we only select the modes 1 and 5 of Table I. Fig. 3 shows a view of the outdoor experimental setup.

In Table II, the minimum and the average ranging errors are shown for different algorithms and setups, for the indoor data, as detailed in the following:

- RSSI method [21] with logarithmic interpolation training by using the received RSSIs for the mode 1 only (LI mode 1);
- proposed Wiener-based solution by using the received RSSIs for the mode 1 only (Wiener mode 1);
- modified-RSSI method with logarithmic interpolation training by using averaged distances computed using all ten modes (LI mode average);
- proposed Wiener-based approach by using the received RSSIs for all the 10 modes (Wiener all modes).

The ranging distances have been computed by taking as inputs the single, i.e., instantaneous, the maximum and the averaged RSSI values over each set of 100 measurements.

The Wiener algorithm, based on exploiting the mode diversity, performs better with respect to the average of the single-mode estimated distances, while the proposed algorithm that uses one mode only performs better than its counterpart that uses the LI, when considering the mean error.

We think that the performance of the algorithms which use only one mode are better, especially in terms of mean errors, than the ones gained by taking into accounts all modes because the number of measurements is too low to represent a sufficient statistic.

To verify this hypothesis, we have derived a more significant number of measurement samples from a simulation model, based on both the indoor and outdoor channel datasets of [14]. We modeled the received RSSI values as a log-normal distribution with mean and variances computed from the experimental measurements. By doing this, it was possible to emulate 1000 samples for the training phase and 10^6 measurements for computing the results shown in Table III, for which the mean values are similar to the fully experimental ones in Table II, for the indoor scenario.

B. Localization Experimental Results

From the previous simulation results, we derive that combining the diversity information coming from the different transceiver modes, it is possible to extract more accurate ranging distances.

We further exploit such results to improve localization performance: we have employed the estimated distances obtained from the instantaneous RSSIs as inputs of a trilateral localization algorithm [18], with a variable number of anchors

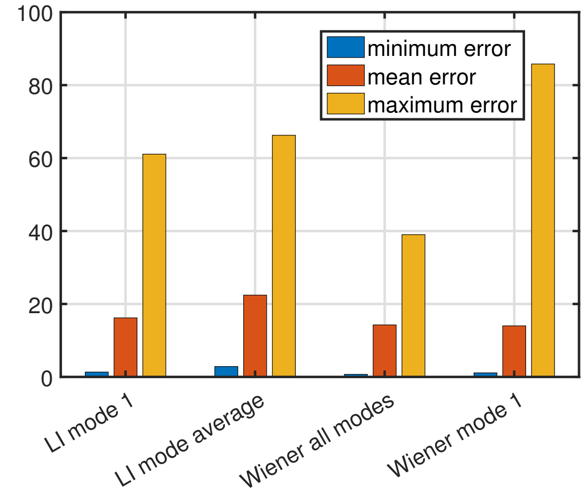

Fig. 4: Experimental minimum, average and maximum localization error (m), using trilateration with 3 anchors, indoor scenario

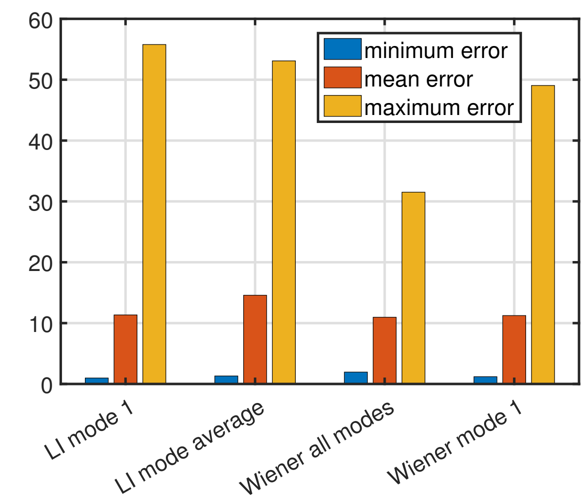

Fig. 5: Experimental minimum, average and maximum localization error (m), using trilateration with 6 anchors, indoor scenario

in the interval $[3, 7]$. The distance between each anchor and the target varies from 1 to 35 m in indoor environment and from 68 to 466 m in outdoor environment as specified in [14]. In this way, the statistical meaning of the experimental data is better exploited.

As shown in Fig. 4-5, the proposed all mode Wiener-based method gives the best localization accuracy results, in terms of the minimum, average and maximum positioning errors, considering 3 and 6 anchors. The same performance trend is confirmed in Fig. 6, where the minimum and mean localization distance errors diminish with increasing number of used anchors.

Since the results of Fig. 6 may suffer from a poor data statistic, the mean distance errors in Fig. 7 and 8 have been computed by using the simulated data set as explained previ-

TABLE III: Average ranging error (in m), indoor simulated dataset

	LI mode 1	Wiener mode 1	LI mode average	Wiener all modes
simulated RSSI	16.1820	16.4527	26.0787	16.5526

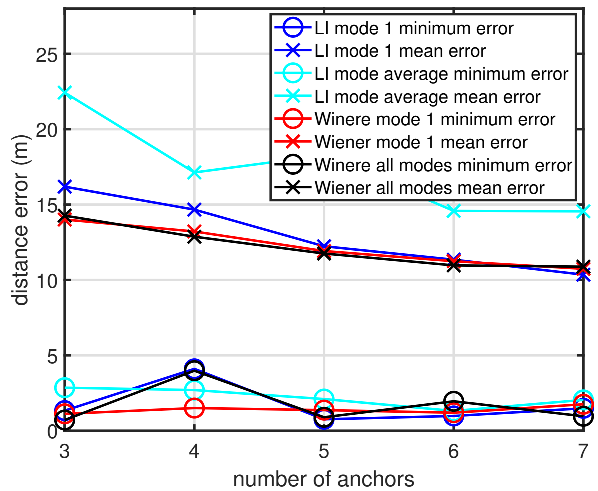

Fig. 6: Experimental minimum and average localization error versus the number of anchors, using trilateration, indoor scenario

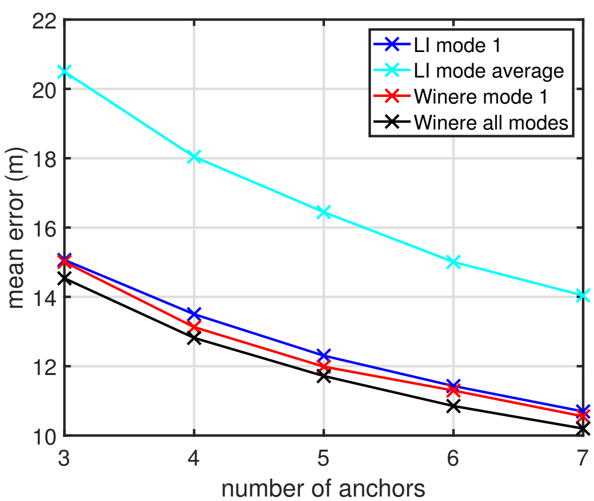

Fig. 7: Mean localization error versus the number of anchors, using trilateration, indoor scenario

ously, for both the indoor and outdoor data sets. The simulated outcomes confirm that the proposed algorithm performs better than the LI one in each configuration. In particular, LI method always performs better in mode 1 than all modes, while the proposed approach show similar better performance in both settings.

Although the accuracy of the presented results may look poor, it is anyway comparable with the more recent literature: as an example, in [23] the authors achieve an indoor localization accuracy of approximately $20-30$ meters, while in [24]

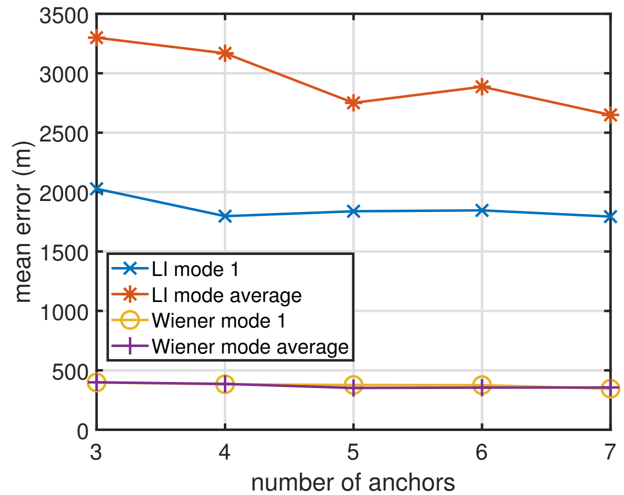

Fig. 8: Mean localization error versus the number of anchors, using trilateration. Outdoor data mode 1 and 5.

the obtained outdoor accuracy is a few hundred meters (up to 500 m).

As final remark, although the proposed solution in all modes configuration gives the best results, Fig. 4-8 show that similar performance, and sometimes even better, are achieved when using only one mode. This is due to the limited number of real experimental measurements to correctly represent a sufficient statistic. Because of that, as stated before, we have derived a more significant number of measurement samples from a simulation model that is, anyway, derived from the indoor and outdoor real experimental channel datasets in [14]. The results from the so obtained large number of measurements confirm that Wiener all modes performs better than Wiener 1 mode, as shown in Fig. 7, or give the same performance as in Fig. 8, but never worse than single mode. The similar performance refers to the outdoor scenario (Fig. 8), where, in general, RSSI methods are less performant due to the distances larger than in indoor environment. Indeed, since RSSI decays with the distance logarithmic, their values are less trustable for ranging estimate with large value, especially for the LoRa modes with higher code-rates. Thus, we envision future improvements of the proposed algorithm especially for outdoor scenario. In particular, we aim at developing an optimal diversity modes selection by choosing only the filter coefficients with the maximum absolute value, in order not to include the effect of the less performant modes on the final accuracy.

V. Conclusions and Future Works

We have proposed a block Wiener algorithm able to combine the RSSI values received for different LoRa modulation configurations, to improve ranging and localization performance. In the simulation results, we have given more importance to the indoor case for mainly two reasons: the indoor data set is more complete and accurate, and the indoor case is more interesting from the application point of view, since other powerful techniques, like merging the RSSI outputs with a GPS receiver, not always can be applied to indoor environments.

The proposed method may be implemented without any additional extra energy cost for the RSSI measurements, while the complexity of the ranging algorithm may be kept low by using the least mean square (LMS) solution of the Wiener-Hopf equations. Future works will be devoted to extending the proposed Wiener approach to different technologies where similar techniques can be successfully applied, like ultra wide-band (UWB) and passive devices [25], [26].

As further step we aim to increase the algorithm performance by accurately selecting a subset of modes for which the diversity effect is maximum, with a twofold objective of simplifying the algorithm complexity, and gaining, at the same time, improved results. This interesting future development is suggested by the results obtained when using only one mode, taking into account the fact the less performant modes affected the final accuracy with negative effects. In this sense, the best diversity modes may be selected by choosing only the filter coefficients with the maximum absolute value.

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