Experimental TDoA Localisation in Real Public LoRa Networks

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Abstract. The performance of Time Difference of Arrival (TDoA) localisation for outdoor tracking purposes has been experimentally evaluated in 3 different public LoRaWAN networks in two countries. The localisation performance is compared for different networks, environments, devices, gateway density and algorithms. We demonstrate that the most dense network provided the most accurate time difference stamps with a standard deviation of 1.2 to 1.5 μs. Therefore, localisation results were much better on this network when compared to the other networks. For different scenarios (walking, driving) we obtained a median localisation error of 200m and in 90% of the cases this error was less than 450m

Index Terms—**LoRaWAN, TDoA, Localisation.**

1 Introduction

Nationwide public LoRa networks are currently available in different countries. Some of the deployments also keep track of the arrival times of a packet on different gateways. Using a Time Difference of Arrival (TDoA) algorithm enables us to localise sensor nodes in the network. A popular use case or LoRaWAN TDoA is tracking non-powered assets. The advantages of localizing sensors using this technique is the fact that all complexity is shifted to the network side. This keeps the sensors simple, low cost and low power when compared with using GPS. The downside is that the mobile node itself has no knowledge on its location. In [1] a comparison of the performance of different TDoA algorithms on a single public LoRa network (KPN) was performed. A comparable approach was done in the work of [2], but the measurement campaign was performed on a private LoRa network. Unfortunately a maximum likelihood (ML) algorithm was not taken into consideration in these works, although it is shown that ML algorithms outperform many other TDoA algorithms such as the Taylor series, analytical and least squares methods [3][4][5]. Therefore this paper will extend the work of [1] by using a ML algorithm on experimental data gathered from 3 different public LoRa networks in 2 countries. In the work of [6] and [7] the TDoA performance is assessed when considering a single network and a commercial solver. This paper will extend these works by comparing the ML algorithm from [8] with the commercial solver implemented by KPN [11]. To the best of our knowledge the timestamp accuracy on public LoRa networks is not yet quantified in any work. This paper will therefore quantify also the timestamp difference accuracy. In this paper we consider LoRaWAN TDoA localisation on 3 different networks originating from 3 different telecom providers: KPN (Netherlands), Proximus (Belgium) and Wireless Belgium (Belgium). The novelties and goal of this paper are investigating the localisation perfomance for: (i) Different TDoA algorithms: a maximum likelihood TDoA vs a commercial solver. (ii) Different type of networks and environments. Each having a different gateway density deployment and gateway timestamping accuracy. (iii) Different devices within the same network. The paper is organized as follows. In Section II, the TDoA inputs, algorithm and performance quantification are described. Time difference distribution and localisation performance results are discussed in Section III. We summarize our observations and future work in Section IV.

2 Materials and Methods

2.1 TDoA Algorithm

The basic TDoA setup is as follows: A mobile node at location (X, Y) transmits a packet. This packet is received by $N \geq 4$ gateways which accurately record the time of the incoming packets: $t_1, t_2, ..., t_i, ..., t_N$ are the timestamps for gateways 1 to N with locations (X_k, Y_k) $\{k = 1...N.\}$. The next step is to calculate the time differences $dt_{i,j} = t_i - t_j$. with j as reference and $i = 1..N, i \neq j$. The N gateway locations together with the $(N-1)$ time differences are used as input for the ML TDoA algorithm. Each of the N nodes is used once as a reference node, for which the ML TDoA algorithm calculates the resulting ML location L_j:

$$L_j = ML(dt_{1,j}, ..., dt_{i,j}, ..., dt_{N,j}) \; i \neq j, j = 1..N \tag{1}$$

The ML algorithm operates by minimizing a cost function. For more details we refer to [8]. To minimize outliers caused by selecting a less well synchronized reference gateway, the final ML location is estimated as the median (in X and Y) from all N previous estimated locations:

$$L = median(L_1, ..., L_N) \tag{2}$$

For each of the scenarios we calculate the error between the estimated location and the GPS location, which is considered as ground truth. Next, we determine the error cumulative distribution function (CDF). From these CDFs the median and 90th percentile error metrics can be obtained. For the KPN scenarios we will also compare this ML TDoA with their integrated commercial solver[11].

2.2 Gateway Locations, timestamps and scenarios

Fig. 1 shows the network deployment of the LoRaWAN gateways for the 3 telecom operators. We note that deployment of the gateways is denser in the larger cities. Table 1 lists the available timestamp resolution T_R and number of gateways Nx that have been deployed for each operator. Wireless Belgium and Proximus cover the Northern part of Belgium, while KPN is covering whole of the Netherlands. The area covered (in km^2) by these gateways is also noted in the table. The gateway density D is defined as the average number of gateways per 10km by 10km area (100km^2). Table 1 shows that KPN has a denser network (2.2/100 km^2) than Proximus (1.8/100 km^2) which in turn is more dense than Wireless Belgium (1.2/100 km^2).

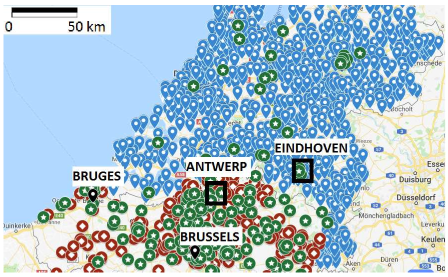

Fig. 1. Gateway deployment of Wireless Belgium (Green), Proximus (Red) and KPN (Blue). The black pointers are the stationary beacons in Bruges and Brussels, Belgium. The black squares denote the measurement area for Proximus in Antwerp and KPN in Eindhoven, the Netherlands

Table 1. Network Deployment Properties for the 3 Networks. T_R is the provided timestamp resolution. Nx is the number of gateways deployed for an area S. The gateway density D is defined as the average number of gateways for an area of 10km x 10km.

Operator	T_R	N_x	S [km^2]	D [#/100km^2]
Wireless Belgium	1 μs	166	14000	1.2
Proximus	1 ns	248	14000	1.8
KPN	1 ns	951	42500	2.2

Accuracy of the provided timestamps is important to obtain an accurate location estimate. The gateways deployed by KPN and Proximus provide timestamps with nanosecond resolution, while only microsecond resolution timestamps are provided by the Wireless Belgium network. This is due to the fact that the gateways deployed by Proximus and KPN are based on the Semtech version 2 reference design [9] vs. version 1 for the Wireless Belgium network. The error

(Δdt) on time difference stamps (dt) is quantified as follows. For each uplink with known transmit location (GPS as ground truth) we estimate all theoretical time differences as follows:

$$dt_{T,i,j} = (d_i - d_j)/c \tag{3}$$

Here d_i and d_j denote the distance between the transmitting device and gateway i, j respectively. c is the speed of the propagating wave and is equal to 3x10^8 m/s. The measured time differences are calculated as

$$dt_{M,i,j} = t_i - t_j \tag{4}$$

with t_i and t_j the timestamps of the received packets on gateway i and j. These time differences are then compared to (subtracted from) the theoretical ones:

$$\Delta dt_{i,j} = dt_{T,i,j} - dt_{M,i,j} \tag{5}$$

In the ideal case, the difference between the measured and calculated time differences is always 0 ns. Due to multipath and synchronization errors we expect this error to be normally distributed. A histogram can be obtained by recording $\Delta dt_{i,j}$ for each uplink for a particular gateway combination i and j. The total obtained (Δdt) histogram can be obtained by considering all combinations of i and j. For the different networks and scenarios this histogram is given in Section III. For each of the 3 networks, two different (A and B) measurement campaigns were performed leading to a total of 6 datasets. Table 2 lists a description of the scenarios.

- In the network of Wireless Belgium, 2 stationary TX beacons A and B are considered. The first one (A) is located in Bruges, while the second one (B) is located in Brussels. The 2 beacons are also displayed as black pointers in Fig. 1. A TX beacon is a gateway which is configured to transmit packets. Since these gateways are placed on rooftops, we expect often Line of Sight (LOS) conditions between the beacons and RX gateways. Therefore a high number of gateways (50+) received the TX packets from the stationary beacon(s). The beacons were configured to transmit on spreading factor 12 with a new transmission every 10 minutes. Data was collected over a meaurement period of 18 hours.
- In the Proximus scenarios, two LoRaWAN devices were provisioned in the Proximus LoRa network, which were attached to Bpost (Belgium Post) cars driving around in the city of Antwerp. These devices were configured to transmit a packet with their GPS location every 30 seconds during a data collection time of 4 days. The used spreading factor was not fixed but was controlled by the network with the use of ADR (Adaptive Data Rate). We refer to [10] which describes in detail how the Proximus data was obtained. In the Proximus network we measured and obtained data during 4 full days.
- In the KPN network the transmitting device was first placed inside a car, driving in and around Eindhoven in the Netherlands (KPN scenario A) . The GPS ground truth was logged with a smartphone. Next, we carried the

device during a walk to obtain data for the last scenario (KPN scenario B). The device was configured to transmit packets every 15 seconds. In order to comply with the ETSI duty cycle regulations (1%) on the 868 MHz band we fixed the spreading factor to SF9 for this device. For the KPN scenarios the data was logged in less than one hour.

The datasets from the 6 scenarios were compressed to a useful format only containing uplinks received by 4 or more gateways. The number of uplinks (samples) which were received by 4 or more gateways N_{RX4} can be found in Table 2. Since the data collection time of the Proximus scenarios was much longer than the other scenarios, more useful samples were obtained. For each of these uplinks the arrival time of the packet is known at the gateways. The location of those gateways is also available with known latitude and longitude coordinates.

Table 2. Measured scenarios with description, used Spreading factor SF and configured interval between transmissions. N_{RX_4} is the number of obtained uplinks which were received by 4 or more gateways.

Measurement campaign	Interval	SF	N_{RX_4}
WB A(Stationary Beacon)	600s	12	106
WB B(Stationary Beacon)	600s	12	106
Proximus A(Car trajectory)	30s	ADR	1140
Proximus B(Car trajectory)	30s	ADR	663
KPN A(Car trajectory)	15s	9	54
KPN B(Walk trajectory)	15s	9	42

3 Results

3.1 Time-difference errors

Fig. 2 shows the error (Δdt) on time differences (dt) in histograms for the scenarios considered in Table 2. The histograms ranges were set from -20 to +20 μs with time difference bins of 1μs. From these plots we see that the timing error is normally distributed with a median of 0 μs. The standard deviations (spreading of the obtained histogram) are 3.9/3.9μs, 1.8/3.1μs and 1.2/1.5μs for the Wireless Belgium, Proximus and KPN scenarios A/B, respectively. Therefore, the most accurate timestamps were obtained from the KPN network, hence we expect the localisation performance on this network to be better than the other networks. The least accurate timestamps are obtained from Wireless Belgium. This is due to the fact that the different networks use different types of gateways. We note that Proximus timestamp accuracy is less than that of the KPN network altough V2 Gateways were used like in the KPN network. This is part of further investigation but might be caused by the environment (multipath).

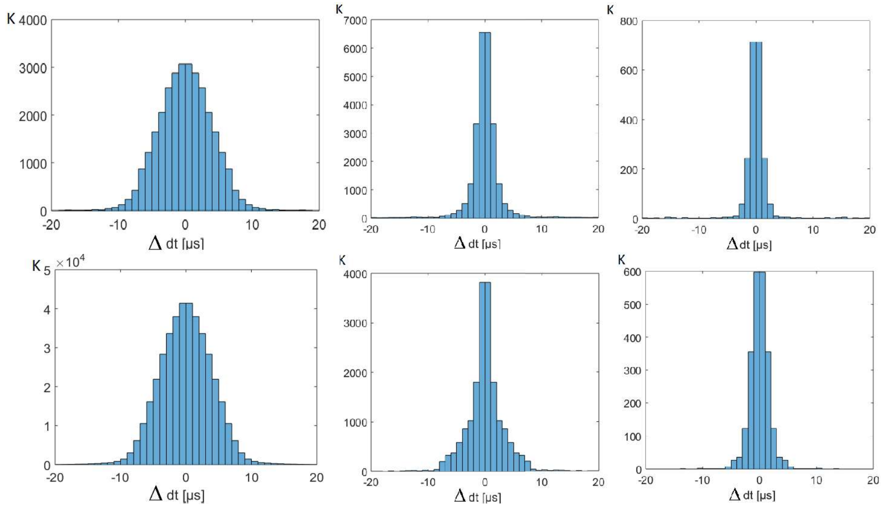

Fig. 2. Histogram of errors on time differences for Wireless Belgium (left) Proximus (Middle) and KPN (right). The top and bottom figures are set A and B respectively

3.2 Error CDF when using ML TDoA algorithm

Fig. 3 (left) shows the localisation error CDF for all 6 scenarios. As predicted from the timestamp errors and gateway density (Table 1), localisation on the KPN network is far more accurate when compared with the other 2 networks. We can rank the networks according to their (median) localisation accuracy as follows. KPN (200m), Proximus (340m), Wireless Belgium (>400m). The obtained accuracy is directly related to the provided timestamp accuracy as given in the previous subsection. The (90th percentile) errors on these networks are as follows: KPN (400m), Proximus (800m), Wireless Belgium (1000m). Again, these differences between networks can be explained by the provided timestamp accuracy. We do note a special case where the Wireless Belgium B (WB B) scenario is almost as good as Proximus (A and B). This can be explained by the fact that WB B uplink data was received (on average) by far more (50+) gateways from its (high) stationary Line of Sight (LOS) transmit location. This is in contrast where the number of gateways that received a packet was always less than 10 for Proximus and KPN.
From the CDF it is further shown that the KPN A and KPN B with different mobility (driving and walking) have similar localisation performance. Therefore the mobility of the scenario does not have much impact on localisation performance. The median (p50) and 90th percentile (p90) errors for the different scenarios are summarized in Table 3.

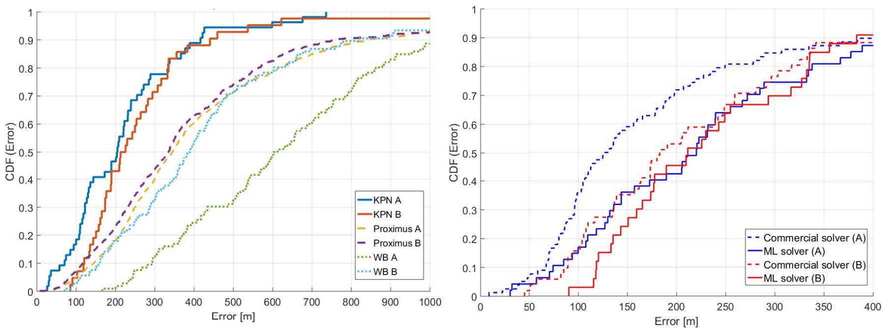

Fig. 3. Left:Error CDF for the different scenarios when using a ML TDoA algorithm. Right:Comparison of ML versus commercial solver on the KPN network

Table 3. Localisation Error quantification for the different scenarios (A/B)

Metric/Network	ML WB	ML Proxi B	ML KPN	Commercial KPN
p50 [m]	610/390	340/330	200/220	130/180
p90 [m]	1100/820	840/750	420/450	400/410

3.3 ML versus commercial TDoA solver

Apart from the timestamp data obtained from KPN, we also extracted their TDoA localisation estimates. This allows us to compare the ML algorithm with their (black box) solver. In Fig. 3 (right) both approaches are compared for both A and B scenarios. Table 3 summarizes the localisation results. The commercial solver from [11] performs better than the ML algorithm: the median error for the ML algorithm was 220m and 200 for the KPN A and B scenarios while these errors (130m and 180m) were less for the commercial solver. We believe this is a combination of a few causes such as timestamp outlier removal and a different approach for selecting the best reference gateway. We also did not yet combine TDoA with RSSI data and postprocessed the localisation results. From the CDFs we noted that the ML approach was as good as the commercial solver in case the 90th percentile errors are considered: all errors were around 400m irrespective of solver used and mobility scenario.

4 Conclusion

The accuracy of obtained time-difference stamps was investigated for 3 different public LoRa networks: Wireless Belgium, Proximus and KPN. Accuracies of these time differences were quantified by the standard deviation which is ranging between 1.2 and 3.9 μs. The measured scenarios on the KPN network had the most accurate timestamping. This immediately impacted the TDoA localisation results: the KPN localisation results were significantly better than on the other networks. A median accuracy of around 200m was obtained on this network with the maximum likelihood algorithm. In 90 percent of the cases the error was less than 400m. Our investigation also showed that the mobility of the node did not significantly impact the raw TDoA localisation accuracy. Future work includes selection of the best reference gateway and perform only localisation with a subset of timestamps by removing outliers[12][13][14]. Combinations of TDoA with signal strength and Angle of Arrival data are also part of future research. We will also investigate map-matching with sensor fusion (such as embedding a compass) techniques to further improve the localisation results.

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