5G NR UL SRS TDoA Positioning by OpenAirInterface

Mohsen Ahadi[1], Adeel Malik[2], Florian Kaltenberger[3] and Cedric Thienot[4]

[1,2,3] *EURECOM,Campus SophiaTech, 450 Route des Chappes, 06410 Biot, France*
[4]*Firecell, 21 Av. Thiers, 06000 Nice, France*

Abstract
Utilizing cellular signals for User Equipment (UE) positioning becomes appealing where accurate positioning through global navigation satellite systems (GNSS), such as indoors, is impractical. The 5G New Radio (NR) standard, developed by 3GPP, has introduced advanced functionalities to facilitate the precise positioning of user terminals. In this work, we present a proof of concept for a 5G NR positioning system architecture based on OpenAirInterface (OAI) as well as a position estimation algorithm based on Particle Swarm Optimization (PSO) using UpLink Time Difference of Arrival (UL TDoA) of Sounding Reference Signal (SRS). TDoA is a widely used parameter for horizontal positioning that does not require synchronization between base stations and mobile stations. The simulation in this work is carried out on OAI RFsimulator. OAI is open-source software that includes UE and gNB implementations of 3GPP Release 16. The results from OAI RFsimulator validate the PSO position estimation accuracy of 1m with the minimum required number of Line of Sight (LOS) gNBs where there is no GNSS link or prior information available.

Keywords
5G Positioning, TDoA, OpenAirInterface, PSO

1. Introduction

Mobile device location information provides significant information that may be exploited to create new applications and services, such as Industry 4.0 and the Internet of Things (IoT)[1]. This data might potentially be utilized to help wireless providers improve network performance. However, precise location estimation using GNSS is not achievable in indoor conditions where there is no Line of Sight (LOS) to a satellite. New capabilities in a 5G NR Stand Alone (SA) signal in conjunction with the 5G NR positioning architecture, can be used to create an accurate indoor positioning system [2]. The 5G NR positioning architecture from 3GPP release 16 is composed of three major layers: 5G Next Generation Radio Access Network (5G NR-RAN), 5G Core Network (5G-CN), and User Equipment (UE) [3]. The architecture is depicted schematically in Figure 1. All the communications between 5G-RAN and 5G-CN have to go through Access and Mobility Function (AMF) first. The location Management Function (LMF) in the 5G-CN estimates the UE position, based on measurements acquired from gNBs. This information is transferred from gNB to LMF by the New Radio Positioning Protocol Annex (NRPPA), an extension of the LTE Positioning Protocol (LPP). gNB can measure several parameters of the received signal from

Proceedings of the Work-in-Progress Papers at the 13th International Conference on Indoor Positioning and Indoor Navigation (IPIN-WiP 2023)
mohsen.ahadi@eurecom.fr (M. Ahadi); adeel.malik@eurecom.fr (A. Malik); florian.kaltenberger@eurecom.fr (F. Kaltenberger); cedric.thienot@firecell.io (C. Thienot)

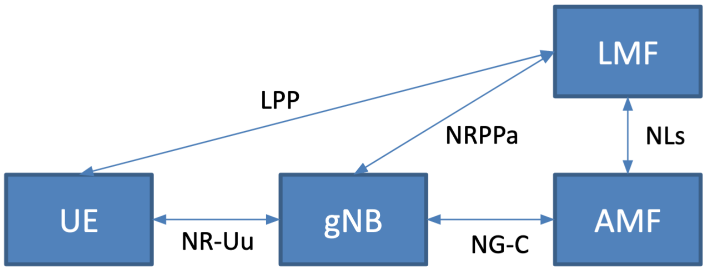

Figure 1: 5G NR Positioning General Architecture

a UE to estimate its position. Received Signal Strength (RSS) measurements as in [4], [5] are sensitive to rapid and gradual signal fluctuations, resulting in less precise localization estimates. Time of Arrival (ToA) based positioning in [6] and [7] offers accurate horizontal coordinates (x, y), but demands precise clock synchronization between the gNBs and the UE. In contrast, Time Difference of Arrival (TDoA) systems overcome the need for clock synchronization at the point of interest or UE by considering the differing arrival times of UE UpLink (UL) signals on multiple gNBs [2]. However, it's important to note that clock synchronization is still necessary among all gNBs in TDoA-based positioning schemes. The selected measurements are transferred from gNB to LMF to estimate the UE's position.
The main contribution of this work is proposing a 5G NR positioning architecture prototype and algorithm developed on OAI. In this work, TDoAs of UL Sounding Reference Signal(SRS) from a nr UE to multiple gNBs are measured on OAI RFsimulator and transferred to an emulated LMF on Matlab using MQTT protocol acting as NRPPA. In LMF, a new algorithm based on Particle Swarm Optimization (PSO) is utilized to solve the set of non-linear and non-convex positioning equations using TDoA measurements. This algorithm is a heuristic global minimum search method that requires only the minimum number of LOS gNBs with fast convergence and real-time UE position estimation. We evaluate the performance of the algorithm using the RFsimulator on OAI with a hybrid geometry-based stochastic channel model. The results show that PSO performs user positioning with 1m accuracy in 80% to 90% of the cases in FR1 and a sub-meter (Root Mean Squared Error) RMSE with the minimum number of LOS gNBs. Also, a link to the demonstration of this prototype is available at the end of the results section.

2. Related work

There are several options to solve the non-linear and non-convex positioning equations on LMF. Maximum Likelihood Estimation (MLE) can handle non-linearity if the model and measurements follow a known distribution which is not a practical assumption. However, it may struggle with highly non-linear systems, and for complex models with numerous local minimums, it may require optimization techniques to overcome the non-convexity as in Semi Definite Programming (SDP)[8] and Second-Order Cone Programming (SOCP)[9] by relaxing the non-convex equality constraints. Generally, in all SDP solutions, when the size of the problem increases, the dimension of the matrix cone increases simultaneously and the number of unknown variables increases non-linearly which makes it computationally complex. Extended Kalman Filter (EKF) in [10] linearizes the model and measurements using Taylor series expansions, making it suitable for systems with moderate non-linearity. However, it may encounter difficulties in accurately representing highly non-linear systems. Also, it requires an initial estimation as well as a motion model to predict the user's mobility. Particle Filter (PF) [11] is well-suited for non-linear and non-Gaussian systems as it does not rely on linearization. It can handle highly non-linear models and measurements. However, PF is generally more computationally intensive compared to MLE and EKF due to its sampling and re-sampling steps. To have a robust estimation based on previous methods, one needs several redundant anchor points with known positions and Line Of Sight (LOS) to ensure a fine initial estimation to start the above algorithms. Also, MLE, EKF, and PF are not specifically designed for local minimum search as they are primarily used for estimation and filtering tasks. Moreover, some related work on developing 3GPP standard positioning systems is carried out. Such as measurements in [12] that rely on OpenAirInterface (OAI) gNB and UE implementations. However, a simplified position estimation method is carried out based on the multilateration of TDoA hyperbolas with low accuracy. In [13] by clustering the indoor area, first a TDoA algorithm is used to determine a coarse target location to identify the UE's cluster. Then, a fingerprinting approach is investigated using RSS measurements on OAI eNB for LTE networks. In [14] LMF is designed in alignment with the latest 3GPP standard requirements that are integrated within OpenAirInterface (OAI). They investigate the latency of the location network function services. However, this development has not yet merged with the OAI RAN network and does not show the performance with different positioning algorithms.

3. OAI RFsimulator-Based 5G NR Positioning Prototype

3.1. Network Environment: OAI RFsimulator

OpenAirInterface5G (OAI5G) is an open-source software platform that provides a complete implementation of the 5G Radio Access Network (RAN) protocol stack. It is designed to be flexible, modular, and adaptable to a wide range of use cases and deployment scenarios. The platform includes software components that implement the physical layer (PHY), medium access control (MAC), radio resource management (RRM), and higher-layer protocol stack functions. RFsimulator is a software module within the OAI5G platform that simulates the behavior of the 5G radio frequency (RF) front end. It is a key component of the OAI5G system, as it enables researchers and developers to simulate the behavior of various RF parameters, such as carrier frequency, bandwidth, noise figure, and amplifier gain without the need for physical hardware. In this work, nrUE and multiple gNBs can be simulated in the RFsimulator to transmit and receive UL-SRS over different available channel models. For each UL transmission, one slot containing SRS symbols is received on multiple gNBs simultaneously which models the tight synchronization assumption among them. This can be verified by logging the equal peaks of channel impulse response on each gNB.

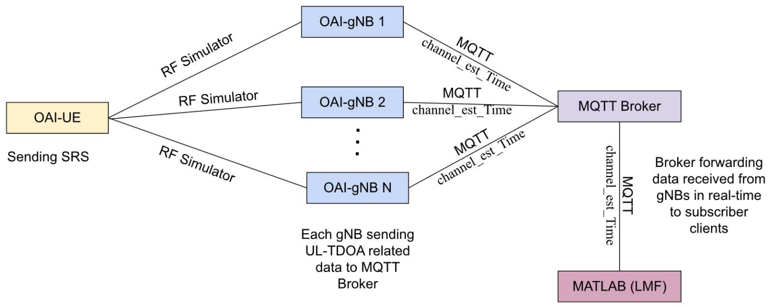

Figure 2: Proposed network and protocol diagram

3.2. UE Mobility: OAI Telnet Server

Telnet server refers to a server that enables interaction with the OAI software components to configure parameters, monitor network performance, and perform various administrative tasks. Since it is possible to modify the channel time offsets corresponding to each UE-gNB pair by telnet server, arbitrary UE positions in the network can be modeled. A simple script containing random UE positions and selected gNB coordinates enables the telnet server to change each gNB-UE channel time offset accordingly in RFsimulator. On each gNB, this can be observed as different impulse response peaks in the time domain which account for the signal's ToAs. Each ToA is sent from OAI gNBs to the Matlab environment acting as the LMF using MQTT protocol acting as NRPPA.

3.3. Emulating NRPPa

NRPPA transfers gNB channel estimations to the LMF as well as useful information such as gNB's TRP (Transmission and Reception Point) coordinates that are assumed to be known for solving the positioning equations in LMF. The estimated position information then can be also transmitted to the UE. Since the standard NRPPA is currently under development at EURECOM, here for the proof of concept, we use MQTT (Message Queuing Telemetry Transport) which is a lightweight messaging protocol designed for IoT (Internet of Things) and M2M (machine-to-machine) communication. It is designed to be simple, efficient, and reliable, and can be used over a range of network transports including TCP/IP, Bluetooth, and other wireless networks. MQTT is based on a publish/subscribe messaging model, where clients (or devices) can publish messages to topics, and other clients can subscribe to those topics to receive the messages. This protocol consists of two main components: the broker and the clients. The broker is a server that acts as an intermediary between the publishers and the subscribers. It receives all messages from the publishers and routes them to the subscribers based on their subscriptions. Here the UE acts as the server while multiple gNBs are subscribed to the "Channel Estimation" topic over a broker server that forwards the channel estimations containing ToAs from OAI gNBs to LMF in Matlab.

3.4. Emulating LMF

Location Management Function refers to the collection of network functions in 3GPP standards that are responsible for tracking and controlling the position of mobile devices inside a cellular network. Since LMF is not integrated into OAI so far, in our work we imitate its functionality and estimate the UE's position in the Matlab environment. In the UL-TDoA positioning method, the UE position is estimated based on differing multiple UL-ToA measurements from a UE on different TRPs along with other configuration information. To obtain UL measurements, the TRPs need to know the characteristics of the SRS signal transmitted by the UE for the period required to perform the UL measurement. These characteristics should be static over the periodic transmission of SRS during the UL measurements. Hence, the LMF requests the serving gNB to direct the UE to transmit SRS signals for UL positioning. It is up to the serving gNB to make the final decision on resources to be assigned and to communicate this SRS configuration information back to the LMF so that LMF can forward the SRS configuration to the TRPs. The current OAI code does not support all the functionalities of LMF and localization-related protocols. Therefore, we adopted several simplifications and developed our prototype shown in Figure 2 to replicate the real functionalities described above.

4. Signal and System Model

4.1. UL NR SRS

SRS is a UL reference signal that is periodically broadcast by a cellular network's user equipment (UE). It allows the gNB to estimate the radio channel characteristics from a UE such as RSSI, multipath delays (ToA/TDoA), or angle information as Angle of Arrival (AoA) when multiple antennas are available. SRS has been improved in 3GPP Release 16 in comparison to prior versions. Support for more bandwidths, enhanced power management methods, and the addition of new triggering mechanisms that allow the network to request an SRS transmission from a UE under particular conditions[15]. These modifications are intended to improve cellular network overall efficiency and performance, particularly in high-mobility settings. In the time domain, SRS can be set to use 1/2/4 symbols among the final six symbols in the slot. Up to 272 resource blocks (RBs) in the frequency domain can be used for SRS broadcasts. UE can employ a transmission comb with sizes 2 and 4 between subcarriers.

4.2. TDoA Estimation with Oversampling

Given an SRS received signal on each gNB where $Y_{srs}[n]$ is a received complex symbol value, $X_{srs}[n]$ is a transmitted complex SRS symbol, and $H_{srs}[n]$ is a complex channel gain experienced by a symbol, all for $n \in \{1, ..., N_{fft}\}$ and N_{fft} is the symbols length or FFT size. The received signal in the frequency domain is given by

$$Y_{srs}[n] = H_{srs}[n] \cdot X_{srs}[n] + W[n], \tag{1}$$

where $W[n]$ is an Additive White Gaussian Noise (AWGN). Then, the least squared estimation of the channel response on SRS symbols takes the form

$$\hat{H}_{srs}[n] = \frac{Y_{srs}[n]}{X_{srs}[n]}. \tag{2}$$

To minimize the effects of noise on the channel estimates, the least square estimates are averaged using an averaging window. In order to get a fine time of arrival estimation of SRS symbols in the time domain, an Inverse Discrete Fourier Transform (IDFT) with order L oversampling is carried;

$$\hat{\mathbf{h}} = L \times \mathrm{IDFT}\left([\hat{\mathbf{H}}(1 : \frac{N_{\mathrm{fft}}}{2}), \mathrm{zeros}(1, L \times N_{\mathrm{fft}} - N_{\mathrm{fft}}), \hat{\mathbf{H}}(\frac{N_{\mathrm{fft}}}{2} + 1 : \mathrm{end}])\right) \tag{3}$$

The Inverse Discrete Fourier Transform (IDFT) is defined as:

$$x[n] = \frac{1}{N_{fft}} \sum_{k=0}^{N_{fft}-1} X[k] \cdot e^{j2\pi \frac{kn}{N_{fft}}}, \tag{4}$$

where $x[n]$ represents the time-domain sequence, N is the total number of samples, $X[k]$ denotes the frequency-domain sequence, and $e^{j2\pi \frac{n}{N}}$ is the complex exponential term. Each term in the summation represents a complex exponential at a different frequency index, which when combined, reconstructs the time-domain sequence. The strongest peak taken from the impulse response on each gNB is assumed to be the ToA estimate after multiplying to the sampling rate $S_r = N_{fft} \times SCS$, where SCS is the Sub-Carrier Spacing. However, as long as there is no common reference time between the UE and gNBs, we convert the N ToAs to $N-1$ TDoA with the 1st gNB assumed to be the reference.

4.3. System Model

Taking $\mathbf{x} = (x, y)$ as the UE coordinate, the system of position equations can be written in a vector as follows:

$$\mathbf{f}(x, y) + \mathbf{e} = \mathbf{r} \tag{5}$$

where $\mathbf{f}$ contains $(N-1)$ equations for N gNBs (with $N-1$ time difference observations):

$$\begin{aligned} f_{TDoA,n}(x, y) &= r_n - r_1 = r_{n1} \\ &= \sqrt{(x - x_n)^2 + (y - y_n)^2} - \sqrt{(x - x_1)^2 + (y - y_1)^2} \end{aligned} \tag{6}$$

In the above equations, $\mathbf{a}_n = (x_n, y_n)$ is the n^{th} gNB coordinate and r_n is the distance between the n^{th} gNB and UE. Here r_1 is the reference gNB's measured range that the UE is synchronized to and has the strongest received signal which is assumed to be the nearest gNB with a LOS. The objective is to find an optimized estimation for UE's position $\hat{\mathbf{X}}$ that satisfies the cost function below with range difference measurements $r_{n1} = \{r_{21}, r_{31}, ..., r_{N,1}\}$ between $N-1$ gNBs and the reference gNB 1 relative to the UE's position.

$$\hat{\mathbf{X}} = \min_{\mathbf{X} \in R^{2\times 1}} \sum_{n}^{N-1} \quad (r_{n1} - (\| \mathbf{a}_n - \mathbf{x} \| - \| \mathbf{a}_1 - \mathbf{x} \|)^2 \tag{7}$$

5. PSO Position Estimation in LMF

Particle Swarm Optimization solves the positioning non-linear equations from the previous section, by employing a population of points (swarm) in a D-dimensional search space[16]. Unlike other approaches that seek to linearize equation (6), which adds extra noise to the position estimate, the swarm of points will directly fit into the non-linear cost function (7). At each iteration, k, the algorithm updates the velocity $\mathbf{v}_k^i = [v_k^i(x), v_k^i(y)]$ and position $\mathbf{x}_k^i = [x_k^i(x), x_k^i(y)]$ of each particle in every dimension and records the particles' individual best ($\mathbf{p}^i$) and the swarm's global best ($\mathbf{p}^g$) positions. The swarm after several iterations converge to the global minimum cost function error. The particle's position and velocity update at each iteration following the simple equations below;

$$\mathbf{v}_{k+1}^i = w\mathbf{v}_k^i + c_1 r_1(\mathbf{p}_k^i - \mathbf{x}_k^i) + c_2 r_2(\mathbf{p}_k^g - \mathbf{x}_k^g), \tag{8}$$

$$\mathbf{x}_{k+1}^i = \mathbf{x}_k^i + \mathbf{v}_k^i. \tag{9}$$

Finally, after k iterations when the termination condition $k = K_{max}$ is passed, the best global position will be returned as the UE estimated position. The constants $c_1 = 0.5$ and $c_2 = 0.9$ are adjusted as the searching rate between the individual best ($\mathbf{p}^i$) and the global best ($\mathbf{p}^g$) respectively. c_2 needs to be greater than c_1 for the swarm to converge. The inertia weight on the previous velocity is a constant set to $w = 0.5$. r_1, r_2 are random numbers between 0 and 1.

Algorithm 1 Particle Swarm Optimization (PSO) Algorithm

```
Initialize particles with random positions and velocities
Initialize the global best position p_g and fitness f_g in (7)
while termination condition is not met do
    for all particles do
        Update particle's velocity using Equation (8)
        Update particle's position using Equation (9)
        Update particle's fitness
        if particle's fitness is better than f_g then
            Update p_g to particle's position
            Update f_g to particle's fitness
        end if
    end for
end while
Output: The global best position p_g and fitness f_g
```

6. Simulations and Results

To test the accuracy of the proposed positioning algorithm on LMF, UL SRS from 200 random UE positions are transmitted and their ToA on multiple gNBs are estimated on RFsimulator. The measurements are transferred to LMF and converted to TDoA to be used in PSO. Two

Table 1
Simulation configuration details

Parameter	Value
Channel Model	Ricean
Scenario	Indoor Factory Hall LOS
Simulation Size	$120m \times 60m \times 10m$
Carrier frequency	3.3 GHz
Sub Carrier Spacing	30 KHz
Number of PRBs 1	106
Number of PRBs 2	272
Sampling rate 1	61.44×10^6 Sample/sec
Sampling rate 2	122.88×10^6 Sample/sec
number of gNBs	3, 4, 6, 8
number of random UE positions	200

different SRS configuration is used with 106 and 272 Physical Resource Blocks (PRBs) that gives 61.44×10^6 samples/sec and 122.88×10^6 samples/sec respectively. The details of signal and simulation configurations are presented in table 1.
Figure 3 compares the PSO positioning accuracy to the Non-Linear Least Squares (NLS) solved by the Gauss-Newton's method[17] that is initialized by a Linear Least Squares (LLS) coarse estimation. Both results are based on UL TDoA measurements from the minimum number of LOS gNBs ($N = 4$) to have a unique solution. This shows in the case of only a few LOS links available, PSO as a stochastic optimization solution, overcomes the non-linearity and non-convexity of position equations better than the others. while conventional methods either non-linear like WLS, NLS, EKF, or linear like LLS require initialization from GPS or a redundant number of anchors, PSO outperforms them in estimation error by utilizing a population of points in the search space to converge to the global minimum. Simulation results give $RMSE_{NLS} = 1.7047$ and $RMSE_{PSO} = 0.7463$ that shows a significant improvement.
Although with 3 gNBs and 2 TDoA measurements, the 2D position estimation is theoretically possible in many cases, according to the geometry of the problem since three hyperbolae may intersect in two points, it can be shown that a unique solution for the position equations requires at least 4 gNBs in TDoA method [18]. The results from adding redundant gNBs validate this in figure 4 where the 3 gNB setup has a major error difference in comparison to 4, 6, and 8 gNBs. Finally, results from figure 5 confirms the fact that utilizing a larger signal BW to have a higher sampling rate, gives a better TDoA estimation that ends up improving the UE position estimates significantly. A video demonstrating how OAI RFsimulator works with 4 gNBs and a UE, and how LMF on Matlab performs position estimation based on TDoAs is available on this URL: https://drive.google.com/file/d/1_C8lk3Yr27INYVdLomFUTELu3g5C2tK9/view?usp=sharing

7. Future Work

To take a step further and test this prototype and the proposed positioning algorithm with real deployments, a setup is organized at EURECOM. This setup includes a QUECTEL 5G module as UE that sends UL SRS to 4 USRPs(Universal Software Radio Peripheral) as distributed TRPs

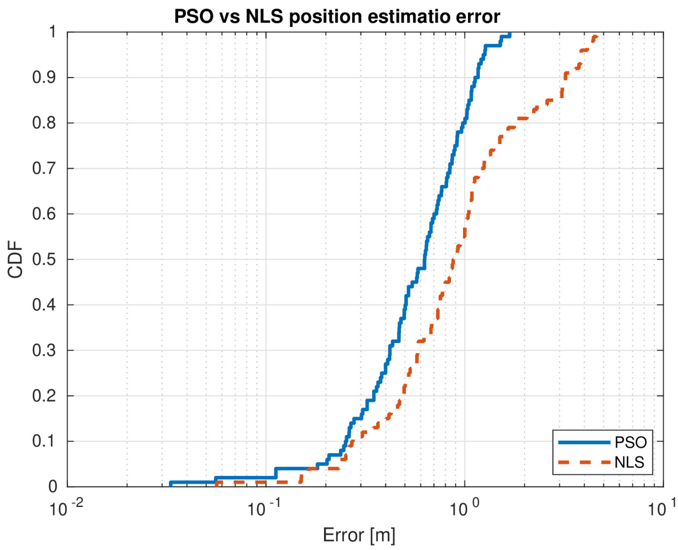

Figure 3: 4gNB PSO and NLS position estimation error

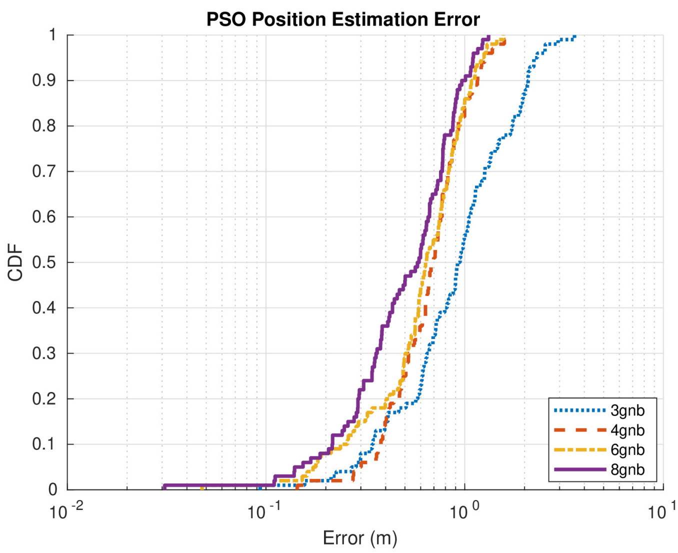

Figure 4: Positioning Improvement by redundant gNBs

connected to a single gNB with OAI software running. USRP is a hardware platform that enables the development and implementation of SDR (Software-Defined Radio) systems. It consists of a motherboard with programmable components and daughter boards that can be configured for various wireless communication standards. Therefore, There are 2 USRPs of model N300 and 2 USRP of model N310 that is synchronized with an external clock of a grand master taken from a GPS module. A diagram of this setup is shown in figure 6. It follows the

Figure 5: 4gNB with 106 and 272 PRB SRS configuration error

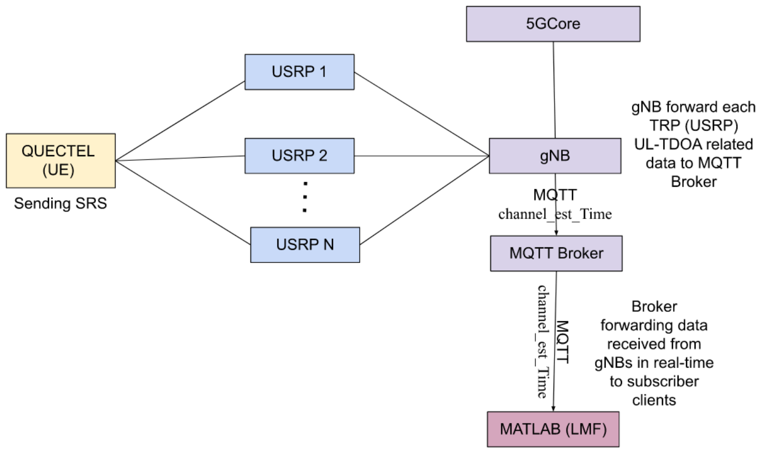

Figure 6: 4 USRP Setup diagram

same principles in architecture and positioning algorithm as proposed in RFsimulator with similar MQTT as NRPPA and Matlab as LMF emulations. At the time of writing this paper, the USRPs are successfully synchronized and receive the UL SRS ToA peaks simultaneously with a consistent TDoA for a UE position. It is planned to test this prototype setup at an Indoor Factory Hall (InFH) that represents the standard 3GPP 38.901 InFH channel model scenario [19].

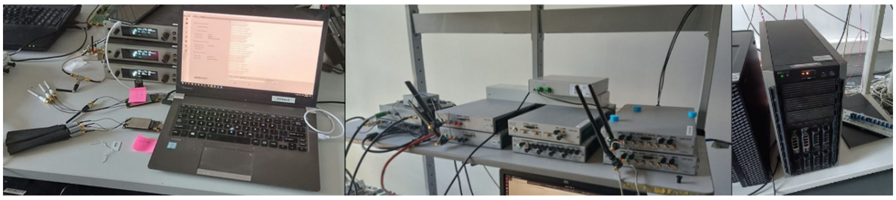

Figure 7: synchronized setup from left with the UE module, multi USRPs connected to the grand master clock by a switch and the gNB machine

8. Conclusion

In this paper, we derived an UpLink Time Difference of Arrival (UL TDoA) position estimation system using Particle Swarm Optimization (PSO) method on OpenAirInterface (OAI) which is a 5G NR 3GPP release 16 compliant software. The algorithm measures an accurate TDoA of Sounding Reference Signal (SRS) by oversampling from a nrUE with an unknown position to multiple synchronized gNBs with known positions and sends this information from gNBs in OAI to the Location Management Function (LMF) model implemented in Matlab using MQTT protocol to act as NRPPA that shows the standard behavior of an online positioning system. The simulations carried on OAI RFsimulator show the PSO position estimation performance using the minimum number of LOS gNBs needless of GPS initialization or error statistics, can achieve around 1 meter accuracy in 90% of cases.

Acknowledgments

The work included in this paper has been supported by the "France 2030" investment program through the projects 5G-OPERA and GEO-5G.

References

[1] D. Wang, G. Hosangadi, P. Monogioudis, A. Rao, Mobile device localization in 5g wireless networks (2019).

[2] R. Keating, M. Säily, J. Hulkkonen, J. Karjalainen, Overview of positioning in 5g new radio, in: 2019 16th International Symposium on Wireless Communication Systems (ISWCS), Oulu, Finland, 2019, pp. 320–324. doi:10.1109/ISWCS.2019.8877160.

[3] 3GPP TS 38.305, 5G; NG Radio Access Network (NG-RAN); Stage 2 functional specification of User Equipment (UE) positioning in NG-RAN, Technical Report, 3GPP.

[4] P. Tarrio, A. M. Bernardos, J. A. Besada, J. R. Casar, A new positioning technique for rss-based localization based on a weighted least squares estimator, in: IEEE International Symposium on Wireless Communication Systems, 2008.

[5] T. Stoyanova, F. Kerasiotis, C. Antonopoulos, G. Papadopoulos, Rss-based localization for wireless sensor networks in practice, in: 9th International Symposium on Communication Systems, Networks and Digital Sign (CSNDSP), 2014.

[6] T.-K. Le, N. Ono, Closed-form and near closed-form solutions for toa-based joint source and sensor localization, IEEE Transactions on Signal Processing 64 (2016).

[7] N. H. Nguyen, K. D. anc ay, Optimal geometry analysis for multistatic toa localization, IEEE Transactions on Signal Processing 64 (2016).

[8] R. M. Vaghefi, R. M. Buehrer, Cooperative localization in nlos environments using semidefinite programming, IEEE Communications Letters 19 (2015) 1382–1385. doi:10.1109/LCOMM.2015.2434393.

[9] G. Naddafzadeh-Shirazi, M. B. Shenouda, L. Lampe, Second order cone programming for sensor network localization with anchor position uncertainty, IEEE Transactions on Wireless Communications 13 (2014) 749–763. doi:10.1109/TWC.2013.122113.130303.

[10] A. R. Destiarti, P. Kristalina, A. Sudarsono, Mobile cooperative tracking with rssi ranging in ekf algorithm for indoor wireless sensor network, in: 2016 International Conference on Knowledge Creation and Intelligent Computing (KCIC), 2016, pp. 60–66. doi:10.1109/KCIC.2016.7992649.

[11] W. Wang, D. Marelli, M. Fu, Dynamic indoor localization using maximum likelihood particle filtering, Sensors 21 (2021) 1090. doi:10.3390/s21041090.

[12] I. Palamà, S. Bartoletti, G. Bianchi, N. B. Melazzi, 5g positioning with sdr-based open-source platforms: Where do we stand?, in: 2022 IEEE 11th IFIP International Conference on Performance Evaluation and Modeling in Wireless and Wired Networks (PEMWN), 2022, pp. 1–6. doi:10.23919/PEMWN56085.2022.9963853.

[13] J. He, H. C. So, A hybrid tdoa-fingerprinting-based localization system for lte network, IEEE Sensors Journal 20 (2020) 13653–13665. doi:10.1109/JSEN.2020.3004179.

[14] A. Pinto, G. Santaromita, C. Fiandrino, D. Giustiniano, F. Esposito, Characterizing location management function performance in 5g core networks, in: 2022 IEEE Conference on Network Function Virtualization and Software Defined Networks (NFV-SDN), 2022, pp. 66–71. doi:10.1109/NFV-SDN56302.2022.9974927.

[15] 3GPP TS 38.211, 5G; NR; Physical channels and modulation, Technical Report, 3GPP.

[16] J. Kennedy, R. Eberhart, Particle swarm optimization, in: Proc. Int. Conf. Neural Netw. (ICNN), Perth, WA, Australia, 1995, pp. 1942–1948.

[17] M. Ahadi, F. Kaltenberger, 5g nr indoor positioning by joint dl-tdoa and dl-aod, in: 2023 IEEE Wireless Communications and Networking Conference (WCNC), Glasgow, United Kingdom, 2023, pp. 1–6. doi:10.1109/WCNC55385.2023.10119056.

[18] Toa and doa based positioning, in: Handbook of Position Location: Theory, Practice, and Advances, IEEE, 2019, pp. 197–198. doi:10.1002/9781119434610.part2.

[19] 3GPP TR 38.901, 5G;Study on channel model for frequencies from 0.5 to 100 GHz, Technical Report, 3GPP.