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Twin Transition for The Timber Industry

Deliverable 2.7 Initial AI-Driven Edge Computing and Precise Localization Demonstrator

5G-TIMBER | Work Package 2, Task 2.4

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Glossary of Terms and Abbreviations

Abbreviation / Term	Description
3GPP	3rd Generation Partnership Program
5G	5th Generation
AGV	Automatic Guided Vehicle
AI	Artificial Intelligence
AOA	Angle of Arrival
AOD	Angle of Departure
AP-TWR	Active-Passive Two-Way Ranging
AR	Augmented Reality
CSI	Channel State Information
DAS	Delay and Sum
DL	Downlink
DNN	Deep Neural Network
DoA	Description of Action
DOA	Direction of Arrival
DT	Digital Twin
E-CID	Enhanced Cell ID
FR	Frequency Range
GA	Grant Agreement
GPS	Global Positioning System
gNB	g-Node B, 5G NR base station
GNSS	Global Navigation Satellite System
IEEE	Institute of Electrical and Electronics Engineers
KPI	Key Performance Indicator
L1	Layer 1 – Physical Layer

L3	Layer 3 – Network Layer
LCS	Location Service(s)
LOS	Line of Sight
LTE	Long-Term Evolution
MAC	Media Access Control
MA-DRL	Multi Agent Deep Reinforcement Learning
MEC	Mobile Edge Computing
MIMO	Multiple Input Multiple Output
ML	Machine Learning
MUSIC	MUltiple SIgnal Classification
MVDR	Minimum Variance Distortionless Response
NLOS	Non-Line of Sight
NPN	Non-Public Network
NR	New Radio
OAI	Open Air Interface
OCC	Optical Camera Communications
ONN	Operational Neural Network
O-RAN	Open RAN
PRS	Positioning Reference Signal
RAN	Radio Access Network
RAT	Radio Access Technology
RAR	Random Access Response
RBS	Recursive Bayesian Filtering
RIC	RAN Intelligent Controller
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality

RSSI	Received Signal Strength Indicator
RTLS	Real-Time Locating System
RTK	Real-Time Kinematics
RTT	Round-Trip Time
RU	Radio Unit
SDR	Software Defined Radio
SLAM	Simultaneous Localization and Mapping
SPRE	Simultaneous Position and Reflector Estimation
SS	Synchronisation Signal
SSB	Synchronization Signal Block
SSS	Secondary Synchronisation Signal
SVM	Support Vector Machine
TA	Timing Advance
TOF	Time of Flight
TS	Technical Specification
UC	Use case
UE	User Equipment
UL	Uplink
USRP	Universal Software Radio Peripheral
UWB	Ultra-Wideband
UX	User Experience

1. Executive Summary

The purpose of this deliverable is to give an overview of how the indoor positioning solution will be provided for the relevant use-cases (UCs) within 5G-TIMBER project.

At first a brief overview of the goals and intermediate results of other similar, 5G-related projects is provided for comparison.

The deliverable brings out the issue about unavailability of hardware, like radio network elements and user equipment (UE), supporting 5G based positioning. Alternative approaches are explored and the most suitable ones are recommended as temporary solutions. Those temporary measures are to be used until 5G-based positioning becomes feasible. Hopefully this happens during the timeline of the ongoing project.

Topics of edge computing, machine learning and non-line of sight (NLOS) detection are covered briefly as they all are related to either enabling positioning or improving its accuracy, availability, and update rate.

To test the use cases demanding accurate indoor positioning during the project lifetime, an ultra-wideband (UWB) based solution is the most viable option and should be used. As one of the goals is to provide the 5G-based solutions for all manufacturing needs, including indoor positioning, then work on enabling 5G based positioning is also continued as well.

Radio Access Network (RAN) provided at the first phase of the project by the partners is not suitable for 5G RAN dependant positioning due to this the involvement of mobile network provider Elisa with its own RAN equipment is necessary. With such involvement, a Downlink Angle of Departure (DL-AOD) method is the most suitable candidate for 5G RAN dependent positioning solution at the beginning of the project. Uplink Angle of Arrival (UL-AOA) method should be implemented in the later phase if the necessary equipment (either from the project partners or Elisa), becomes available.

Overall, both time- and angle-based methods will be tested. Precise positioning data will be offered at RAN intelligent controller (RIC) to exploit positioning for various purposes (e.g., predictive handovers, interference management etc). Necessary computational resources for implementation of positioning solutions, including capability to support Machine Learning (ML) solutions must be available at the network edge. Demand arises as the positioning results are often time-critical.

2. Introduction

5G-based positioning could be a suitable solution for all the positioning needs in the 5G-TIMBER project. In practice, however, the necessary hardware, capable to perform any kind of 5G RAT (5th generation Radio Access Technology) dependent positioning, is not yet commercially available. Timing-based methods will need capability to transmit the Positioning Reference Signals on the RAN side and receive them on UE side. Neither capability is jet available. There are operational 5G NR base stations (gNB) in market capable of transmitting Synchronisation Signals in different directions for angle-based positioning. But there are not yet UE capable of measuring those signals.

Until fully commercial solutions will be available, there are at least three possible alternative solutions that can be considered. The first one, included already in the initial proposal, is the use of cameras and edge processing of their signals for indoor positioning. Secondly, we can use the commercially available Ultra-Wideband (UWB) indoor positioning technology as a temporary replacement for timing-based 5G positioning. UWB system can also be later used as a means to obtain ground truth for validation of the performance of the 5G based positioning system.

Although we have no access to dedicated 5G positioning hardware we can still use what is available, although probably with limited performance. This would be mainly possible thanks to the use of O-RAN architecture in radio access network that is supplied by the Accelleran. O-RAN allows us to access and use lots of network parameters for positioning purpose. Also, the measurement results or calculated positioning estimates from other systems, such as cameras or UWB, can be forwarded to the RAN to be used by the positioning application (xApp) running in near-real time Radio Access network Intelligent Controller (RIC).

Within the current project, the use of the location services (LCS) are expected from three UCs. The main one is UC2.1 - Precise localization for production processes optimization and human safety. LCS are also planned also to be reused for UC2.2 - DT, AR and Industry 5.0 UX assisted production supported by ZSM 5G data exchange and for UC2.3 Data driven design to production cycle optimization. All of them belong to the second UC category - Modular wood-house factory. More in-depth explanation of UCs can be found in Deliverable 1.1 "Initial Descriptions of Use Cases with Expected Outcomes and Impact Projections to 3 Target Domains."

Harmet factory production hall is approximately 230 m long and 100 m wide. General shape- and size of the factory building is shown in Figure 1. There are no internal walls, but the floor level is crowded with manufacturing lines and modular houses in different states of completion. There are also rows of columns supporting the roof and cranes operating below it. Knowledge of shape and size of the manufacturing building simplifies the positioning task, as all results that will fall outside the building can be automatically discarded. On the other hand, as the houses are built and moved around the factory, then the environment is constantly changing and thus complicating the positioning task.

The initial deployment will be single radio unit (RU) operating at n77u band (3.7 - 4.2 GHz). A second deployment will contain three mm-wave gNBs. The frequency range for non-public 5G networks (NPN) in Estonia is 24.3 to 24.7 GHz. This range can possibly be utilized later in the project when mm-wave equipment becomes available.

KPIs for positioning accuracy are given in D1.3 where it is stated that the target is to achieve a generic localization accuracy of between 100 cm and 500 cm (robust for predictive handover etc.) and between 20 cm and 50 cm for the safety-oriented localisation accuracy.

Production process optimization or predictive handover scenarios will probably require absolute positioning – coordinates related to some predefined origin within factory premises. On the other hand, if we want to avoid the forklift running over a worker, then we are actually interested in their relative positions against each other. In such case, a relative positioning solution could be a better choice and could also be expected to be more accurate. Camera signals can be analysed with object detection software to estimate possible hazardous solutions without the need for actual positions of objects (worker, forklift, crane).

2.1. Mapping 5G-TIMBER Outputs

This section maps the components described in the 5G-TIMBER's Description of Action (DoA)/Grant Agreement (GA), i.e., the description of the deliverable and task description in the DoA/GA, against the chapters included in this deliverable and the justification of the work conducted in the project. For more detail please see table 1 below.

Table 1 Adherence to 5G-TIMBER's GA Deliverable & Tasks Descriptions

5G-TIMBER GA Element	5G-TIMBER GA Element Outline	Respective Document Chapter(s)	Justification
DELIVERABLE			
D2.7 INITIAL AI-DRIVEN EDGE COMPUTING AND PRECISE LOCALIZATION DEMONSTRATOR	In overall, WP2 deals with the implementation of 5G TIMBER, distributed architecture. This involves the federation, integration and interoperability middleware, the edge-to-cloud storage and computing mechanisms, the core service orchestrator and the involved cyber-security, synchronization and 5G issues. **Specifically, the task behind D2.7 is T2.4 "AI-driven edge computing and precise indoor localization".**	The whole deliverable is dedicated to the topics of the T2.4	The whole document describes possible positioning methods and the selection of most suitable one. Possible uses of AI/ML are also discussed.
TASKS			
T2.4 AI-DRIVEN EDGE COMPUTING AND PRECISE INDOOR LOCALIZATION	Develop new 5G and beyond based positioning algorithms to obtain (cm-level) accuracy. Algorithms for positioning enhancement techniques	Section 4.1 5G Based Positioning, Section 4.3 UWB Positioning,	Describes available, radio-signal based, positioning methods and compares them. Brings out strengths and weaknesses and

	such as suitable antenna distribution (AOA-based methods), cooperative and hybrid positioning, AI-based LOS/NLOS classification method, will be developed at TUT 5G NR localization testbed.	Section 4.4 Mitigation of Multipath- and NLOS Propagation Effects	recommends the use of the most suitable ones.
	Develop enhanced fusion mechanism at the edge for well-beyond 5G to obtain highly reliable cm-level accuracy at low-latency for precise mobile object localization. AI and predictive (Kalman filter-based) mechanisms will be realized to improve the source data quality for fusion enhancement as well as methods among others e.g., dead reckoning will be exploited for obtaining the precise location based on various positioning estimates.	Section 5.2. Fusion of Positioning Data, Section 5.3 Use of AI and Machine Learning	Overviews of possible sensor/data fusion methods is given. AI/ML methods that could be implemented for precise positioning are described.
	Regarding edge computing on the image data, we will develop self-organized ONN with the generative neuron model to optimize different operations for training a network with reduced complexity.	Section 5.1 Edge Computing, Section 4.2 Camera Based Positioning	

2.2. Deliverable Overview and Report Structure

This deliverable starts with a general introduction. This is followed by Chapter 3 giving a brief overview of other similar, 5G based projects; specifically, an overview of the proposed positioning solutions used, or planned to be used in those projects.

The fourth chapter suggests possible positioning solutions that could be adopted during the current project. Chapter 4 is divided into four sections. The first is about 5G-based positioning solutions that could be implemented during the project execution time. The second one gives an overview about camera-based positioning and detection methods. The third one is about the use of ultra-wideband technology for precise indoor positioning. The final, fourth section, addresses general issues arising from the environment where the positioning is taking place, mainly the effects of multipath propagation and Line of Sight (LOS) blocking.

The fifth chapter addresses issues more- or less related to the computational resources. The first section out of three, is about how the edge computing is to be implemented for localization- and safety UCs. A general approach of data fusion for increased positioning accuracy is covered in the second section. Finally, a brief overview of artificial intelligence (AI) and ML methods of choice is provided in last section of Chapter 5.

The sixth chapter concludes the deliverable with a summary and comments.

2.3. Other Project Outputs

This section describes the interdependencies with the other project tasks and activities.

a) Interdependencies between the task(s) of this deliverable and the other WPs:

WP1 provides the initial description of UCs and KPIs for the current task T2.4 "AI-driven edge computing and precise indoor localization." Also. the initial specification of functional and technical requirements of 5G NPN provided by the Accelleran is given in WP1 as an input for the current task and deliverable.

The current task should provide Input to the tasks T3.2 " Design, development and configuration of 5G NPN network infrastructure for the use-cases" and T3.5 "Development of use-cases for wood-based modules manufacturing" of WP3.

In a similar way, the current task should provide input to the two tasks in WP4. The first of them is T4.1 " Infrastructure and IT preparation on Pilot Sites" and the second one is T4.3 "Field trials for wooden houses use-cases."

Work with T2.4 could result in business models and ideas of commercialisation as an input to T5.2 "Business models' development, commercialisation/business plan and commercial acceleration/sustainability" in WP5. It is also possible that standardisation recommendations will arise as inputs for T5.5 "Standardisation recommendations (3GPP/ETSI/ITU/ISO/W3C)."

Possible scientific results of the current task could result in publications. Also, the work on the current task could be reflected both in social- and regular media. In both cases it would be related with the task T6.1 "Dissemination and communication activities" of WP6.

b) Interdependencies between the task(s) of this deliverable and the other -same- WP Tasks:

Task T2.3 "5G NPN network monitoring, close-loop automation for optimization of industrial manufacturing" will share the same 5G network and hardware with planned positioning system.

Table 2 provides a list of the other deliverables that produce inputs to this deliverable or consume outputs from this deliverable.

Table 2 List of the other deliverables that produce inputs to this deliverable or consume outputs from this deliverable.

5G-TIMBER GA Element	Contribution and Value of linkage
Output from D1.1 Initial Descriptions of Use Cases with Expected Outcomes and Impact Projections to 3 Target Domains	Describes use-cases and how positioning is planned to be used within them. Technical feasibility of

	positioning methods and risk management plan.
Output from D1.3 Initial KPIs definition report	Defines positioning KPIs for different UCs.
Output from D1.7 Hardware/software/standard inventory list and blueprint for data sharing	Defines used AI tools and software used for positioning applications.
Output from D1.8 Initial specification of functional and technical requirements of 5G NPN implementations for pilots and beyond	Describes positioning and 3GPP standardisation of it. Brings out positioning-related considerations and issues. Gives overview of used 5G network and its components, including ones that are relevant for positioning.
Input to D2.8 Final AI-driven edge computing and precise localization demonstrator	Current deliverable provides input to the final deliverable of the task T2.4
Input to D3.3 Initial integration report of 5G NPN lab implementation	Current deliverable should provide input about necessary equipment and necessary performance of 5G NPN network for positioning purposes.
Input to D3.9 Initial wooden elements manufacturing pilot use-cases development	Current deliverable as input for planning appropriate test scenarios and setup for those tests.
Input to D4.1 Initial pilot sites setups	Demands for hardware setup for positioning trials.
Input to D4.5 Initial wood house factory pilot report	Inputs for 5G based and hybrid positioning based high precision indoor positioning trial report.

3. Related Projects

This chapter gives a brief overview on solutions used previously in similar projects such as 5G-CLARITY, 6G-BRAINS, and 5G-ROUTES.

One of the topics of the 5G-CLARITY project is high precision positioning. A positioning and synchronization framework based on the combination of 5G/Wi-Fi/LiFi providing cm-level accuracy and real time tracking capabilities [1] is one of the promised innovations of the project. A real BOSCH factory near Barcelona will be used to demonstrate the ability to provide this promised high precision positioning. To be more specific, the use of multiple access technologies, i.e. mm-wave, Wi-Fi, LiFi, and Optical Camera Communications (OCC) will be used to provide an enhanced positioning for Automatic Guided Vehicle (AGV) in the plant.

Sub-6 GHz band is used to estimate Angle of Arrival (AOA) in order to aid directing mm-wave and LiFi links towards AGV (forklift) to be located. TOF method is used in mm-wave frequencies to obtain the range. LiFi is used to locate the mobile vehicle within its limited confined coverage area. OCC will be used to enhance the precision of positioning to detect NLOS and to track moving vehicles. ML algorithm is planned to use for the data fusion obtained from various positioning sensors described [2]. The 5G-CLARITY project has set remarkably high demands for positioning accuracy, as high as less than one centimetre in some cases.

Machine learning is used for LOS/NLOS classification, methods of choice are support vector machine (SVM) [3] and deep neural Networks (DNN) [4]. According to publicly available deliverables of 5G-CLARITY project, this classification is carried out based on Wi-Fi, not 5G signals. Experiments with mm-wave technology are done in laboratory environment and does not include any real 5G technology. Similarly, FR1positioning experiments are made in lab using SDRs with custom signals.

One of the objectives of the 6G BRAINS project is to work out beyond-5G enabling technology for AI-driven data fusion for 3D indoor position mapping through heterogeneous location methods enabling 1 mm location position accuracy and 1° orientation accuracy [5]. Simultaneous Localization and Mapping (SLAM) in three dimensions seems to be a method of choice to reach mentioned ultra-precise performance criterions. Multiple, machine learning related, UCs of this project are expected all to rely on Multi Agent Deep Reinforcement Learning (MA-DRL) framework specifically developed for the 6G BRAINS. Notable contribution to project is 3D laser scanning of whole factory in order to build 3D computer model of it. The constructed model is used for simulations of radio propagation with the ray tracing method [6]. Many interesting, positioning related, testbeds and simulations are described in the public deliverable about 3D location architecture [7]. Uplink TOA testbed is built for example. But this testbed uses custom built hardware not 5G devices, although signals used are generated based on 5G standards. As signals are generated and received by the same device then there are no synchronization issues and thus accuracy, In the order of single centimetre is claimed to be achievable. Positioning is carried out in two dimensions and over an area that is approximately 1-2 m^2 large. Tracking of UE with the base station antenna array beam is also simulated. Tracking itself is based on MA-DRL mentioned above.

The 5G ROUTES project is about 5G connectivity related issues in cross-border situations. Consequently, an indoor positioning is not addressed there. Used positioning methods are 5G assisted RTK GNSS positioning, enhanced cell ID (E-CID) and adaptive E-CID (AECID). First method uses 5G network to forward positioning assistance data from real-Time Kinematics (RTK) ground station to the UE, resulting in the satellite navigation positioning accuracy of few cm under favourable outdoor conditions. Other methods are most suitable for coarse positioning of IoT devices without GNSS module.

4. Positioning Methods

A general description of planned system along with the technical feasibility and risk management plan are described in Section 4.1 of deliverable D1.1. The upper bound for 5G NR based positioning errors for indoor scenarios is 3 m when 3GPP release 16 (Rel-16) compatibility is assumed. This accuracy is within the desired range of 20 - 500 cm. 5G standards, starting from the Rel-16 are describing different positioning methods. Also, the Rel-16 compatible hardware is already available on the markets. Unfortunately, not all functionalities, described in the standards, have to be implemented in every single device. The first interest, and most profitable UCs, for service providers and equipment manufactures is related to the enhanced data rates. Due to that, much development effort has gone there, and the functionality related to positioning is still not yet available at the time of the release of the current report. The issues mentioned here are also brought out in deliverable D1.8 "Initial specification of functional and technical requirements of 5G NPN implementations for pilots and beyond".

The risk mitigation plan for such an unfortunate scenario suggests possible alternative solutions such as the use of cameras or hybrid positioning methods. In D1.3 "Initial KPIs definition report" is also stated that the more available sources for the positioning, the higher confidence and robustness can be expected. It is foreseen to fuse and exploit positioning information from heterogeneous sources (e.g. 5G, UWB, camera) by means of the RAN Intelligent Controller (RIC) and xApp features of the network. Possible different positioning methods and sources are described in more detail below.

4.1. 5G Based Positioning

A general overview of native, 3GPP supported RAT-dependent, positioning methods is given in Chapter 9 of D1.8. In the current section, we do not address all those possible methods but only the ones that could possibly be implemented during the timeline of the project.

In the first phase, at the first quarter of 2023, Accelleran will deploy a single 5G RU. Initially, it will be located at the lab at the TalTech and later moved to the Harmet factory. The RU that will be deployed is the Benetel RAN650 [8] outdoor 4x4MIMO, with 100 MHz bandwidth in n77u band (3.7 – 4.2 GHz).

RAN650 is a 3GPP Rel-15 compatible device, thus it does not have any built-in support for 5G RAT-dependent positioning.

There are still at least two ways to estimate the distance of the user equipment (UE) from the RU. We can use the Timing Advance (TA) parameter T_A to estimate this distance. TA is measured by base station (gNB) and results are sent back to UE for necessary adjustments. When the UE connects to the network, then an initial estimate of TA is forwarded with MAC RAR timing advance command. The initial value of T_A = 0, 1, 2, ..., 3846 and (initial) timing offset is calculated from this as

$$N_{TA} = \frac{T_A \cdot 16 \cdot 64}{2^{\mu}}.$$

This offset is given in units of $T_C = T_S/64 \approx 0.5$ ns. T_s is the basic time unit of LTE, and it is defined as $T_s = 1/(15000 \cdot 2048)$ s, this value is approximately 32.55 ns. During the regular operation, the timing advance command MAC CE, indicates relative timing advance with a 6-bit index value T_A = 0, 1, 2, ... 63. In this case

$$N_{TA,new} = N_{TA,old} + \frac{(T_A - 31) \cdot 16 \cdot 64}{2^{\mu}}.$$

In the above, $N_{TA,old}$ is the current TA estimate and $N_{TA,new}$ is the new, updated value [9]. The resolution depends now also on the numerology parameter μ. As Benetel RAN650 supports only subcarrier spacing of 30 kHz (μ = 1), then the available time resolution would be 256 ns, corresponding to a distance measurement resolution of 76.7 m.

Figure 1 illustrates the principle. The red dot on the left is the location of the gNB, while the dashed lines represent the walls of the manufacturing hall. Red arcs in the figure represent the borders between two different values of TA. As resolution is poor, then this principle allows only to estimate in which third of the factory the UE is located. This simplified figure does not consider the effects of reflections and blocking in TA value.

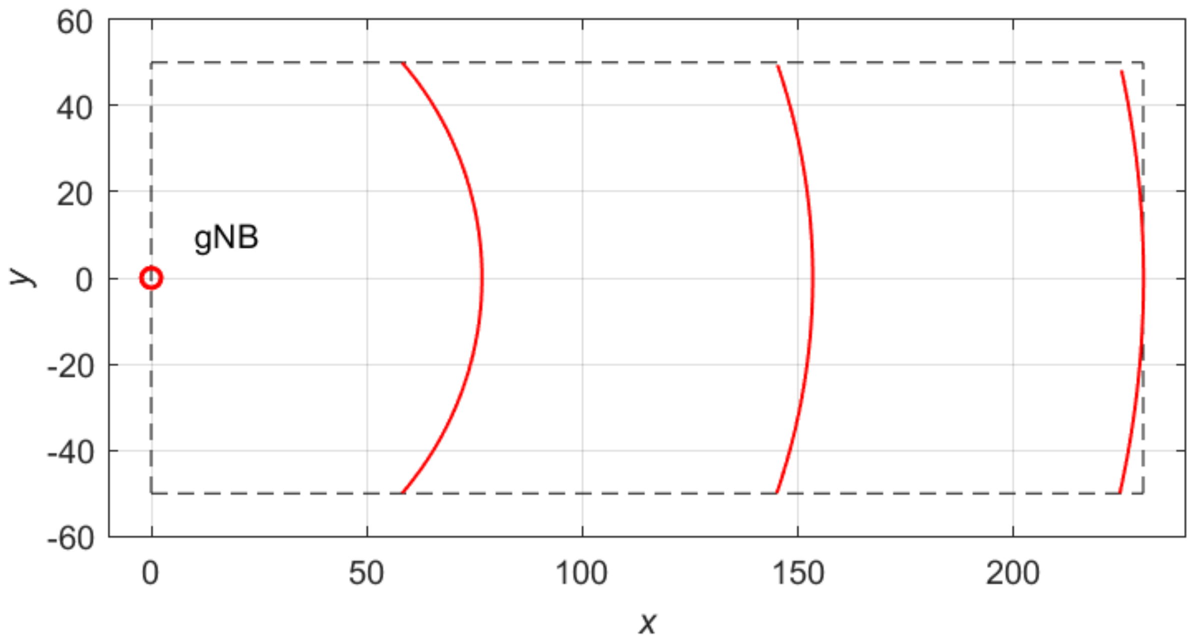

Figure 1. Timing Advance based positioning principle

Distance can also be estimated from the signal power and quality measurements periodically made by all UEs. The signal quality measurements are carried out by the UE on the secondary synchronisation signal. Three distinct measurements have been defined in TS 38.215 [3]. Synchronization Signal based Reference Signal Received Power (SS-RSRP) is defined as the linear average over the power contributions (in watt) of the resource elements that carry secondary synchronization signals (SSS) [3]. As SSS itself is 127 subcarriers wide, then the measurement bandwidth is $127 \cdot 15 \cdot 2^{\mu}$ kHz. The reporting range of SS-RSRP for L3 reporting is defined from -156 dBm to -31 dBm with 1 dB resolution. The reporting range of SS-RSRP (and CSI-RSRP) for L1 reporting is defined from -140 to -44 dBm with 1 dB resolution [2].

Synchronization Signal based reference signal received quality (SS-RSRQ) is defined as the ratio of N×SS-RSRP/NR carrier RSSI, where N is the number of resource blocks in the NR carrier RSSI measurement bandwidth. The measurements in the numerator and denominator shall be made over the same set of resource blocks.

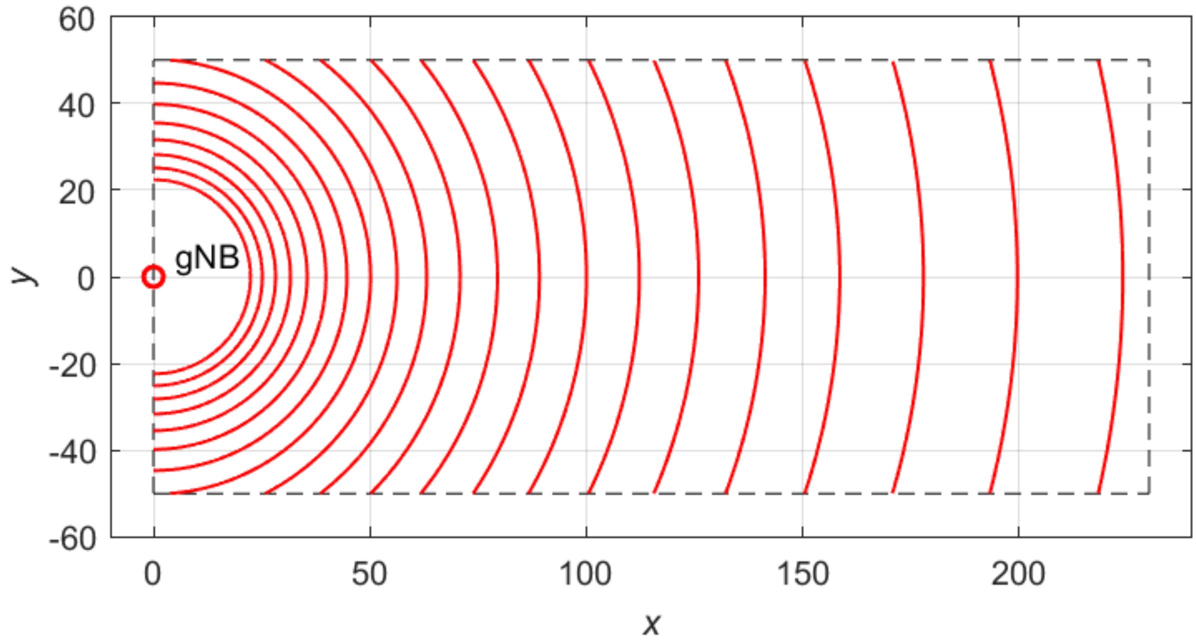

Figure 2. SS-RSRP based positioning principle

In a free space environment, the power measurement resolution of 1 dB would correspond to an increase in distance by approximately 1.122 times. If the UE is too close to gNB, then the signal strength is larger than the maximal measurable value, thus introducing a "dead zone" around the gNB. Starting from some minimal distance, we will get exponentially decreasing measurement accuracy as each next measurable distance is 1.122 times larger than previous. This situation is illustrated in Figure 2 and it is clear that, theoretically, a much better resolution can be achieved here. The depiction here is simplified, assuming free space propagation conditions that are somewhat justified within a large, empty hall. Walls and numerous objects within the actual factory will produce much more complex pattern in real-life scenario. This can be even beneficial as then we could have more than 21 different values that can be used to increase positioning accuracy.

In the second deployment phase, three mm-wave gNBs are planned to be installed in the Harmet factory. The resolution of TA could then be improved up to 32 ns, corresponding to a resolution of distance in order of 9,6 m. As signals with higher frequency are attenuated faster, then there should also be better accuracy in SS-RSRP measurements. With three anchor nodes (gNB) also the position of the UE can already be estimated, and not only the distance to it as it was in case of the single anchor. This estimate can be calculated based on TA value form the serving cell along with RSRP and RSRQ measurements from all cells. Such method is generally known as Enhanced cell ID positioning (E-CID).

An alternative positioning method, that does not rely on geometrical calculations, is known as fingerprinting. In case of fingerprinting, the radio signal values of available base stations are measured at different locations during a calibration phase. Those measurements are then used to build a database for future positioning. If the current location of UE is needed, then same measurements are repeated in specific location and obtained results are compared against the database. Estimate of location is, in the simplest case, coordinates of location where measurements in the database are closest to the ones obtained during the measurement. Some more complex algorithms, such as nearest-neighbour or k nearest-neighbours, can be used in order to increase accuracy.

The disadvantage of the fingerprinting method lays in excessive amount of measurements that have to be performed before the method can be applied. Also, errors will be introduced if there are some changes in the environment after those initial measurements, so in general they must be repeated periodically.

As we have only a single gNB and as the SS-RSRP measurement range is from -156 to -31 dBm with 1 dBm step, then we can have at maximum 125 different values and thus no more than 125 separable locations. If we combine SS-RSRP measurements with TA, we can theoretically triple the number of possible locations up to 375. Even then the optimistic estimate of the average positioning accuracy would be only around 25 m and thus far from sufficient. This is in case of the single RU at the initial deployment phase. Later, when three separate gNBs are available, then the positioning accuracy is expected to increase. If other available signals, such as LTE, WiFi, etc., are also included then further increase in positioning accuracy can be expected.

A basic approach to fingerprinting, as the one briefly described above, is based on searching the nearest match from a database. An alternative approach would be to use collected data for training machine learning algorithm. New measurements, made during the positioning would be then the input of the trained ML algorithm and its output would be estimated location of the UE [11], [12].

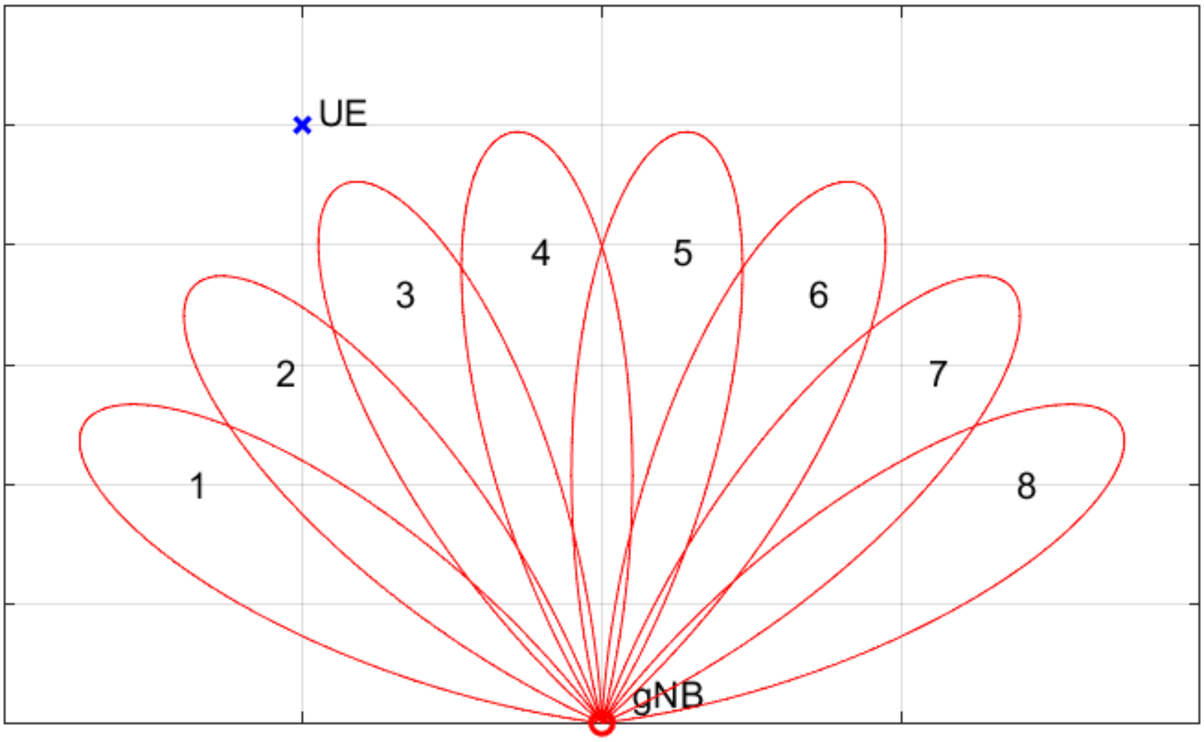

Figure 3. Example of eight separate SSB beams

5G standard supports Synchronization Signal Block (SSB) beam sweeping from the beginning (Rel-15). The base station antenna generates one after another a number of separate, indexed beams, directed at the different directions. Each beam is used to transmit a single SSB block out of an SSB burst.

The maximum number of beams L_{max} (number of SSBs per burst) depends on the used frequency and it can be as high as 64 in FR2. UE can measure signal strength and quality of each separate beam and based on it estimate the Downlink Angle of Departure (DL-AOD) from gNB towards the UE [6], [7]. **Figure 3** shows eight beams generated by the single gNB. From the fingerprinting viewpoint, the availability of the signal parameters of each beam will increase significantly information available for estimating the location of UE.

Local network service provider Elisa is willing to deploy its gNBs (Nokia) in Harmet factory. As they are operating in FR1, then eight SSB beams per sector (up to 180°) can be expected.

If there are 8 different beams in 180° sector, then one beam covers roughly a 22° wide angle. At the maximum distance 230 m, this corresponds to a width of 88 m. It is reasonable to assume that some interpolation can be done in order to get at least few times better angular resolution. The width of a beam is proportional to the distance, so if UE is closer to gNB then we can also expect smaller uncertainty. If FR2 is implemented later in the project, then also larger number of available beams could be expected, each narrower than in FR1.

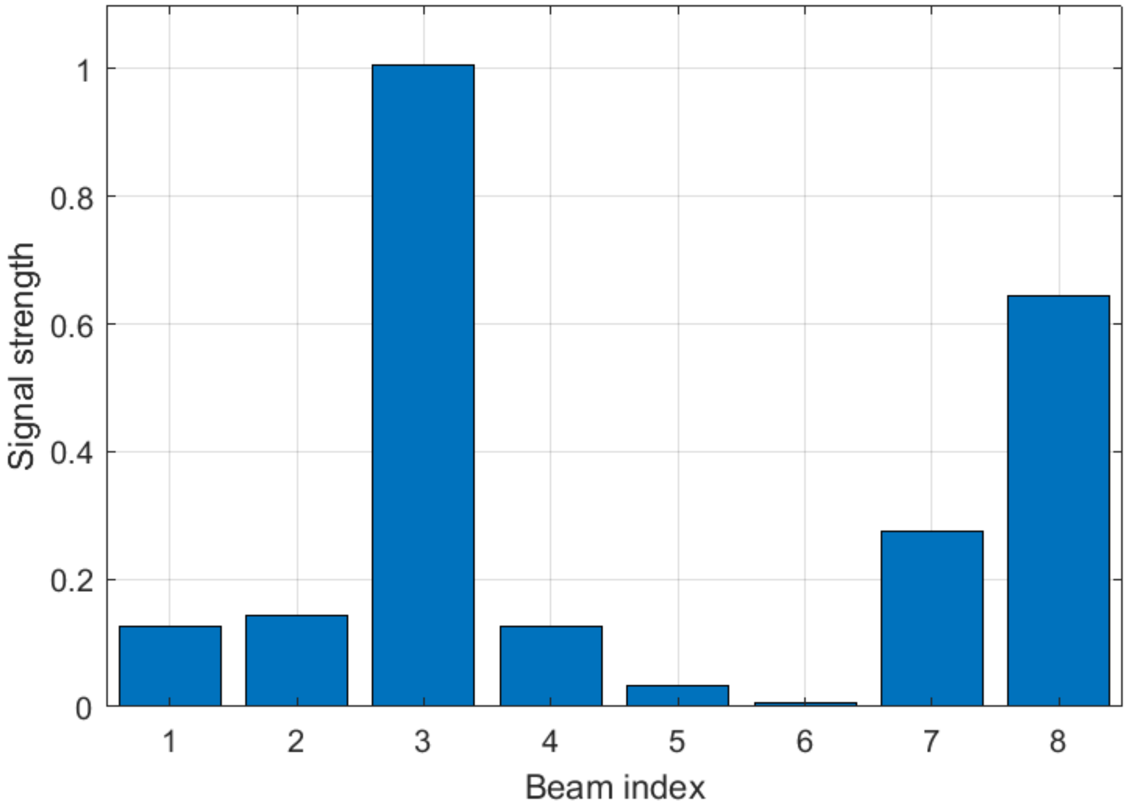

Figure 4. Signal strengths of SSB beams at UE location

The orientation of typical UE is usually random and not known, and those devices cannot contain large antenna array. Due to those reasons, traditional angle measurement methods are not suitable. Instead, the UE measures power of available SSB beams and estimates angle based on that information. If the location of the UE is as shown with the blue x in Figure 3 then measured signal strengths of each beam are showed in Figure 4.

We can see that the strongest signal is coming from the third beam as UE is in the direction of this beam when looking from the gNB. Sidelobes of the antenna, as well reflections in the environment, can also cause strong signals from beams that are looking in completely different directions. For example, the seventh and eight beams in our illustration should not be expected to be with so strong signal as shown. This relationship between the measured and estimated variables is usually not straightforward and thus the machine learning (ML) methods could be useful for this task.

As long as there are no UEs available that are capable of performing and outputting SSB beam measurements, a 5G scanner could be used as an alternative device for the proof of concept. Rohde&Schwarz TSMx series Drive and Walk Test Scanner [4], shown in Figure 5 could be used for this purpose.

Figure 5. Rohde&Schwarz TSMx series Drive and Walk Test Scanner setup [4]

If we have the AOD estimates from at least two separate gNBs, then triangulation can be used to find the UE location estimate. As SSB beams are directed under different angles in horizontal plane, then location estimate is also two-dimensional. This is not a big issue, as UEs are expected to be located near the floor anyway. Still, the different heights of gNBs and UEs must be considered in order to get better location estimate.

Sivers Semiconductors offers different evaluation kits with mm-wave antenna arrays and built-in beam steering functionality. Kit EVK02004 [5] (see Figure 6) has a 4 x 4 planar antenna array that can operate in the range 24,25 to 29.5 GHz thus covering the whole NPN frequency range (24.3 – 24.7 GHz) in the n258 band.

The kit itself contains frequency up- and downconverters and hardware necessary for analogue beamforming. Any signal to be transmitted must be generated in a separate piece of hardware. Possible signal source could be a Software Defined Radio (SDR) like Ettus Research USRP X310 running the OpenAirInterface (OAI) software. One SDR can be used in the role of gNB and a second SDR as a UE.

If the transmission of SSB burst can be synchronized with the beamformer, then SSB beam based positioning method could be implemented in a laboratory setting.

Base stations have fixed location and orientation, and they have large antenna arrays, especially in FR2. The UL-AOA from the UE towards the gNB can be measured with described setup. This functionality is described in standards but not implemented yet. In the best-case scenario, the AOA measuring capabilities can be expected somewhere in 2024. Both elevation and azimuth angles can be measured in such case and thus triangulation can be carried out in three dimensions. If gNBs are suitably stationed, then errors in AOA estimation can be expected to be relatively small.

Figure 6. Sivers Semiconductors EVK02004 evaluation Kit [5]

Sivers evaluation kit, described above, could also be used here in order to test possible direction-finding algorithms and obtainable accuracy. Uniform linear arrays are used for the 5G mobile communication so the Direction of Arrival estimation (DOA) methods suitable for such arrays, as Barlett (DAS), Capon (MVDR) or MUSIC, are the few initial candidates.

Local mobile service provider Elisa is willing to supply the project with Nokia base stations implementing the necessary SSB beamforming. Necessary 5G scanner with beam measurement capability can also be purchased without much delay. Due to that, the DL-AOD method should be preferred as the 5G based solution to start with. In necessary hardware becomes available later, then UL-AOA method should be implemented as a possibly more accurate method.

4.2. Camera Based Event Generation

As 5G positioning is not available in the current 5G release, multi-view camera-based event generation will be used for the worker safety scenarios. Cameras based systems cannot directly provided position information, although it can provide information/prediction about different events of interest.

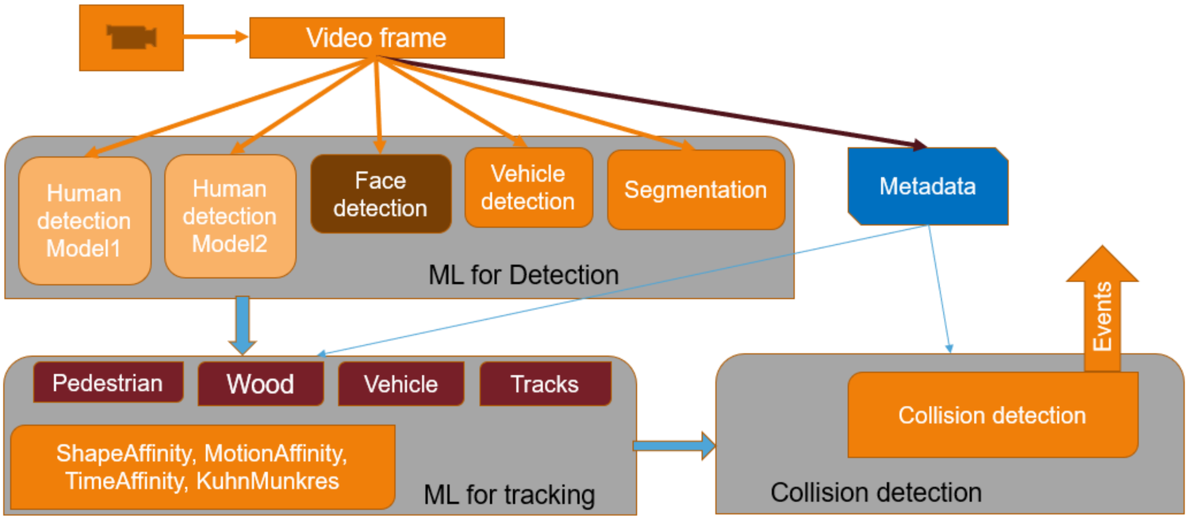

Figure 7. Camera-based event detection

The basic framework of the work safety scenario is shown in **Figure 7**. Frames from the cameras are fed into the different machine learning pre-trained models for the objects (person, vehicles etc.) detection task. The main objective is to detect and track the objects of interest such as humans, vehicles, and other wooden structures for the worker safety. Different affinities are used in the tracking by using Kuhn–Munkres algorithm to solve the assignment problem. A brief description of the different algorithms is described below:

1. Human detector: Different human detectors are used to detect human in each frame and track him or her across different frames. As no detection model is hundred percent accurate, multiple models are used to completed each other.
2. Face detector is used to detect human, but a secondary purpose is to use face expression to detect any potential threat indirectly and generate or check upcoming frames more rigorously.
3. Vehicle detection: provide input for the possible human and vehicle interaction. Therefore detecting & tracking vehicle is important.

4. Instance-segmentation will help to classify each pixel to relevant classes. In normal or routine work, wooden structures are not moving very fast. Segmentation will help to generate event when wooden structures move fast, especially when human are nearby.
5. Tracks are the area of interest where different objects of interest interact with each other. Such as vehicles and human present on the same track. Tracking algorithms generate events when objects (human, vehicles) enter in the restricted areas.

Visual (cameras-based) systems are two dimensional and do not have scene depth information; therefore, we proposed multi-cameras-view to compensate it. Multi-cameras-view will use objects identification and reidentification for tracking and collision detection in multiple views. Single view objects collision can be misleading.

4.3. Ultra-Wideband positioning

Regarding IEEE 802.15.4z UWB positioning, TalTech has been working with the private limited company *Eliko Tehnoloogia Arenduskeskus OÜ* on developing and implementing Real-Time Locating System (RTLS) in the context of several previous and ongoing research projects. RTLS is an UWB-based Indoor Positioning System based on the IEEE 802.15.4z UWB standard [6]. This system can operate from 3.1 to 10.6 GHz with bandwidths at least 500 MHz up to 20% of the centre frequency. As the power spectral density is limited to -41.3 dBm/MHz, then the range of communication is theoretically limited to 200 m. In practice, however, the typical range is more between 30 – 50 m, while ELIKO devices can reach up to 50 – 70 m (70% of the time). A typical setup of this system is presented in Figure 8 below.

The accuracy of Eliko RTLS is better than 10 to 50 cm with a precision in order of 2-3 cm. The update rate of mobile tag position is up to 500 Hz. The distance between tag and fixed anchor nodes is calculated based on measured time of flight (TOF). No synchronization between fixed anchor nodes is needed in such a case. The actual time of flight is estimated from novel Active-Passive two-way AP-TWR ranging method [7] [8]. The general principle of this method is shown in Figure 9.

Ranging is started by the tag (Node A) with sending the corresponding packet. Node B (anchor) replies to it after some processing time t_{B1}. As a third step, node A replies to it after its own processing time t_{A2}. Both of those processing times are measured by the nodes in addition to measuring delays between sending packet and receiving response, t_{A1} and r_{B2}, respectively. The TOF between those two nodes is then calculated, based on those four measurements, as

$$t_{A \leftrightarrow B} = \frac{t_{A1} - t_{A2} + t_{B2} - t_{B1}}{4}.$$

Figure 8. Eliko UWB RTLS system overview

The described UWB positioning system uses typically 500 MHz bandwidth, although it can be increased up to 900 MHz. In FR2, the bandwidth of the signal can be up to 400 MHz. It means that the resolutions in the time domain, and thus also the distance, of both systems are similar. TOF is estimated by measuring the round-trip time (RTT). Also, the 5G standard describes a similar method known as Multi Cell RTT. Signal processing methods of both systems are also expected to be similar in nature. All this indicates that the

UWB positioning system could be a suitable placeholder until necessary the 5G hardware will be commercially available for the project.

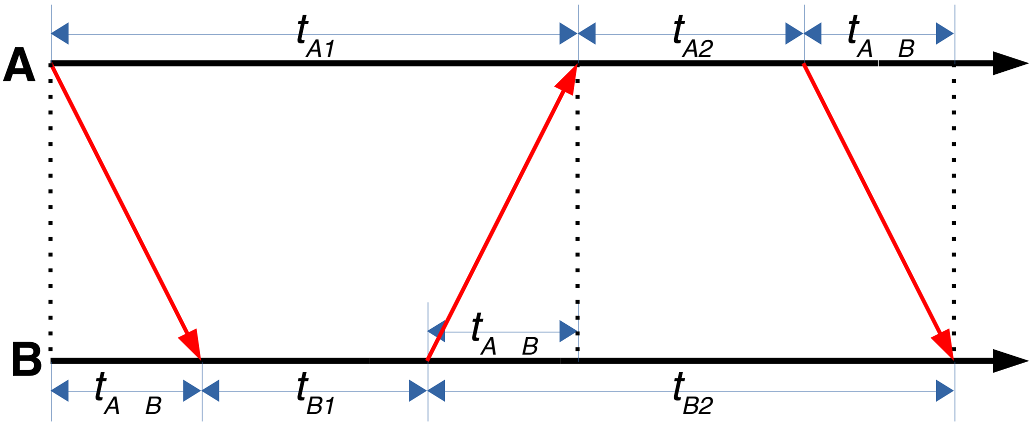

Figure 9. Double sided two-way ranging method

UWB positioning system can be later used as a means to provide the ground truth for validation of 5G RAT - dependent positioning results.

A setup with six anchor nodes can cover an area of approximate size 100 x 50 metres. If the whole Harmet factory is to be covered, then about 30 - 40 anchor nodes are needed in total.

4.4. Mitigation of Multipath- and NLOS Propagation Effects

All mentioned positioning methods will work well in an empty space. Accuracy then would be only limited by the available quality of measurements, and for some methods, also by the precision of time synchronization. However, in real life scenarios, two more hindrances will affect the availability and accuracy of positioning.

The first one is known as multipath propagation. Reflections from the various objects in the environment will cause the same signal to arrive at the receiver multiple times and from different directions. For timing-based solutions this will cause large systematic errors in the distance estimate, and it makes hard to determine actual angles for angle-based systems. The camera-based system can also get confused by the reflections of the objects from reflecting surfaces.

If there is no direct path, i.e. no line of sight (LOS), between UE and anchor of the positioning system, then the signal might get completely blocked. This would be especially true for mm-wave systems and also for cameras that cannot see through opaque objects. Radio signals with lower frequencies will still arrive trough multipath propagation paths; but due to the lack of the LOS path, the errors caused by the multipath will be even more influential.

To combat multipath effects, there are some general and well-known methods. The influence of the delay spread to time delay measurement can be diminished by using signals with large bandwidths. UWB positioning system has a bandwidth of at least 500 MHz, and 5G bandwidth can be as wide as 400 MHz. When base station antennas are positioned far away from possible reflecting surfaces, then also the influence of the multipath to the angle measurement accuracy can be significantly decreased.

In general, the suitable selection of anchor locations can increase both the accuracy and coverage area of the positioning system. If hybrid positioning, by combining several systems is to be used, then sensors of one system can be placed so that they will cover the blind spots of the other one, and vice-versa. If an object is tracked, then it can be predicted when it moves into the shadow for some specific anchor or sensor. Then we can automatically estimate that measurement from this anchor are not be trusted for some time.

As the lack of LOS will generally result in large positioning errors, there has been a lot of work done on both LOS/NLOS classification and NLOS effects mitigation. The classification method of choice depends on what kind of information about the received signals are available. Dedicated UWB positioning systems, like the one described in the current deliverable, are usually measuring additional parameters of received signal and/or propagation channel in addition to the time delay itself. Both the direct utilization of those measurements themselves or the features calculated based on them, allow to perform LOS/NLOS classification. As previously mentioned, additionally measured parameters might be for example as simple as received signal power in general, received power of first (and thus shortest) path, or as complex as a whole channel impulse response. Calculated values can be mean, standard deviation, kurtosis or some other statistical parameter of the received signal. Reading those values from the UWB devices and making necessary calculations can be time consuming and thus as a downside the measurement interval must be increased.

5G radio network does in general only limited measurements like signals strength, quality and signal-to-noise ratio. On the one hand, this means that there are less available parameters to be used for classification. On the other hand, those measurements are made regularly during the normal operation, and they are easily accessible from any terminal. When doing channel estimation, then 5G network actually measures the quality of every single subcarrier within the whole bandwidth. If this data could be accessed, then it could also be used for better classification. Uplink channel estimation is actually done with the same physical reference signal as the uplink positioning so at least theoretically it could be possible to perform two tasks by transmitting the same single signal.

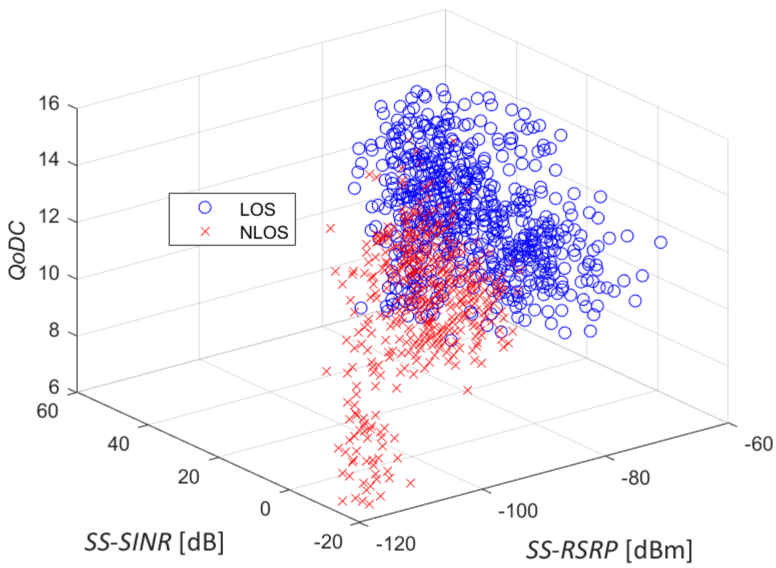

Figure 10. Example of LOS/NLOS classification principle

As relationship between available values and LOS/NLOS decision can be complex then quite popular solution is to use some machine learning algorithm for classification. The authors of current deliverable have also made some successful experiments with ML-aided automatic LOS/NLOS classification of 5G channels.

Figure 10 illustrates the classification task by depicting a three-dimensional cut of measurement results. Measurements indicated with a red "x" are made when there was no direct line of sight between UE and gNB. In same time the measurements indicated with blue circles were made under the LOS conditions. It is quite clear from this figure that those two sets are largely separable from one another.

When we have more measurements available then the minimum needed for unambiguous positioning, then we can simply discard all results that are classified as made under NLOS conditions. If NLOS measurements cannot be discarded, then those less reliable results can be given also less weight in the positioning algorithm.

5. Computational Resources

This chapter addresses issues related to the use of edge computing, positioning data fusion, and the use of machine learning and artificial intelligence in order to enhance the positioning performance.

5.1. Edge Computing

According to its definition, edge computing is a distributed information technology architecture in which client data is processed at the periphery of the network, as close to the originating source as possible. Terms Mobile Edge Computing (MEC) or Multi-Access Edge Computing are used for edge computing in case of mobile communication systems. The main benefit of the MEC for positioning and localisation UCs is low latency. Position estimate is needed as fast as possible, especially in situations where UE has high velocity.

The O-RAN architecture introduces a new software-based network element called the RAN Intelligent Controller (RIC). The RIC is designed to monitor, control and optimise the RAN Network operation. It is involved in controlling and optimising aspects such as radio resource, power, interference and mobility management. The RIC itself consists two components- the non-real-time and near-real-time RICs (non-RT RIC and near-RT RIC). The near-RT RIC manages and events and resources requiring a faster response down to 10 milliseconds. xApps is the term for applications that are developed to control and manage the near-RT RIC. Due to the required response times, the near-RT RIC would typically be deployed on the network edge.

A more detailed description of O-RAN architecture and near-RT RIC can be found in deliverable D1.8 "Initial specification of functional and technical requirements of 5G NPN implementations for pilots and beyond".

The O-RAN architecture is developed with built-in support for AI and ML that can be used in current task for possible improving of the positioning accuracy with data-driven methods.

As edge devices are limited in resources whereas ML methods & algorithms are highly resources demanding. Training a new large ML model on edge

devices is not recommended. It is recommended to optimize a pre-trained model and optionally use hardware accelerates on an edge to efficiently use resources. Efficient use of resources divided into two parts: offline pre-trained model optimization for target edge hardware and online efficient use of hardware resources of the edge. Offline optimizations include post-trained-model parameters quantization, pruning, pre-processing optimization and graph optimization. Offline optimization also considers the target hardware capabilities & architecture to maximize the performance of the model. Efficient use of hardware resources such as vectors instructions and data align for efficient data fetching for the target hardware are vital for maximum performance. The main target of the offline optimization is to make specific pre-trained model align with the target hardware resources and remove unnecessary components from the model such as backpropagation and all temporary variables that are needed only for the training of a model.
Another offline optimization is graph optimization that include constant folding, redundant node eliminations, semantics-preserving node fusions, complex node fusions, layout optimization.

TIETO-FI & TIETO-SE will be using Intel hardware with model precision of INT8 with an accuracy drop threshold from 1% to 5%. For efficient execution on Intel hardware, we will use Intel OpenVINO for performance optimization. We target neural network optimization merging network layers, batch processing, Parallelization at network execution level according to underneath hardware architecture (stream) and reduce the precision of calculation (calibration). Reduction of the calculation precision add nonlinearity that usually contribute toward generalization. Batch size and stream hyperparameter optimization according to the target hardware can provide additional performance boost. NVIDIA is using TensorRT for pre-trained mode optimization and running on NVIDIA hardware accelerators. There are number of hardware execution provider Intel OpenVINO, Intel OneDNN, MS windows DirectML, Qualcomm-SNPE, Android-NNAPI, Apple-CoreML, Android and iOS XNNPACK by Google, AMD-MIGraphX, Cloud-Azure (ONNX runtime) and community maintained are Arm-ACL, Arm- Arm NN, Apache-TVM, Rocksip-RKNPU, Xilinx- Vitis AI and Huawei – CANN.

Additionally, we propose machine learning life cycle management on edges that simplifies the pre-trained model version management on edges. There are multiple options available such as "manage cloud services" from Azure, Google, and Amazon.

5.2. Fusion of Positioning Data

General positioning system outputs the coordinates of the UE at some time instance. In the simplest case this result is calculated based on recent measurements and it does not take previous history into account. Due to measurement errors or unsuitable geometry, those results can sometimes include large errors.

If there is more than one localization system available, then there is a potential for improving general positioning accuracy. Coordinate estimates from all positioning systems, along with their estimated accuracies, can be fused together in order to obtain best available estimate of the actual position of the device under interest. An alternative to such a high-level approach would be to collect all the measurements of all available positioning systems and use them to find the location estimate. Such low-level estimate could be more accurate, but the high-level approach could be easier to practically implement.

Accuracy of the location estimate can also be improved if the previous trajectory and physical limitation of moving object are considered. For example, if a new measurement is further away from the last one than the maximal velocity of a moving object would allow, then we can be sure that there is a large measurement error involved.

A common general approach to track the location of object in time, based on noisy measurements, is Recursive Bayesian Filtering (RBS) or simply Bayesian filtering. Under assumptions that the system is linear and that the measurement noise is Gaussian, we obtain a Kalman filter that is optimal for such a case. Kalman filter is widely used to estimate the state of moving object based on noisy measurements, previous state of said object and model describing its dynamics. Unfortunately, most of real-life systems do not satisfy the conditions of linearity and Gaussian measurement noise.

Extended Kalman filter is a possible solution for nonlinear systems, and it works especially well when systems are near-linear. This solution is the defacto method for navigation systems and GPS. However, if the measurement noise is not Gaussian, then Extended Kalman filter might not perform very well. Particle filtering is alternative solution that can represent arbitrary probability distribution of measurement noise. Kalman filter can be viewed as the exact representation of a simplified model while a particle filter is an approximate representation of a complex model.

Different positioning systems are providing outside information that helps to determine the location of UE. The device can also use built-in sensors to detect the changes in its location internally. The most common sensors are accelerometers and gyroscopes to determine the acceleration and changes in movement direction. Internally collected data can then be fused together with external positioning information in order to increase the positioning accuracy further.

As positioning takes place within limited space and we have access to detailed digital map of the Harmet factory building, then this additional information can and should be also integrated into the fusion mechanism. In the simplest case, we can simply discard location estimates that are falling outside the building area. In more complex cases, the knowledge about the location of reflecting walls and other objects can be used to increase the positioning accuracy significantly [20]. Simultaneous position- and reflector estimation (SPRE) method can be viewed as a version of Simultaneous Localization and Mapping (SLAM) algorithm. SLAM is algorithm, used in robotics, that allows simultaneously generate and update the map of surroundings and simultaneously position a robot on this map. SPRE method, similarly estimates simultaneously the location of the UE and reflectors causing multipath propagation. The algorithm works better if the location of some or all reflectors are previously known, information that can be possibly extracted from available digital maps.

When the system model is well defined, then data fusion can be built on it. If the model is not known, then data-driven solutions like machine learning, could be used instead. The strengths of inductive (data-driven) and deductive (physics-based) approaches can be combined in a single hybrid model. Parts of model that are well known can be implemented directly and estimation of unknown aspect can be assigned to the machine learning algorithms [21].

5.3. Use of AI and Machine Learning

Starting from Release 17, 3GPP is investigating the incorporation of AI/ML-based solutions in the 5G System [22]. Terms of Artificial Intelligence and machine Learning, according to the 3GPP, are defined as follows.

Artificial Intelligence is a general concept defining the capability of a system to act based on two major conditions. The context in which a task has to be done, meaning the value or state of different input parameters and on the past experience of achieving the same task with different parameter values and the record of potential success with each parameter value.

Machine Learning is often described as a subset of AI, in which an application has the capacity to learn from the past experience. This learning feature usually starts with an initial training phase so as to ensure a minimum level of performance when it is placed into service. ML is typically divided into supervised (for classification and regression purposes with prior knowledge) and unsupervised (clustering with no prior knowledge about data categories) learning, and most lately to reinforced learning (acting based on feedback).

Machine learning itself is not some magical tool that solves all problems. There are many situations where either physics-based- or statistical models are well suited to solve problems. ML as data-driven tool is useful in cases where relationships between given inputs and desired outputs is too complex, unknown, or continuously changing. Additionally, a large amount of data for training machine learning models is needed.

The typical solution in case of fingerprinting method is based on database search. Current measurement is compared against the ones in the database in order to find the closest match to it. As all measurements in the database are accompanied by coordinates, then the position of the closest match is the estimate of the current position.

Instead of finding the single best match, a ML algorithm line k-nearest neighbours (KNN) could be used in order to obtain accuracy better than the grid step of initial measurements.

Data collected in training phase can be used to train ML algorithm instead of storing it in database. Inputs of the algorithm would be results of radio signal measurements at given location and outputs would be coordinates of this location. Trained algorithm, for example a neural network, can then later be used to find position estimate based on new measurements in unknown location.

DL-AOD algorithm estimates the angle of departure based on signal strength of measured SSB beams. The number of beams can be anywhere between 4 and 64, based on frequency range and used hardware. In free space the direction of the strongest beam should be a good indicator of the actual directions. In multipath environment those relationships will not be as simple anymore and ML could be one possible solution for finding the estimate of AOD. Inputs of the algorithm would be beam measurements and output the estimated AOD. Alternatively, measurements of beams from two or more gNBs can be used as input while the output is already the estimates of UE location.

If there is NLOS between UE and anchor node (gNB for example), then positioning accuracy will be degraded no matter what method is used. In order to combat this, we need to estimate the lack or presence of LOS path. Some simple solutions could be implemented in simple environments. For example, if there is some blocking object in signals path then the received signal would be weaker then assumed and this can be detected. Better results can be obtained if statistics of received signal parameters are used for classification purposes. ML methods are usually well suited for classification based on complex relationships between input values and classification result.

6. Conclusions

In order to test, during the project timeline, UCs that require high positioning accuracy, the use of UWB-based indoor positioning system is the best currently available solution.

UWB positioning solution is specially designed for indoor positioning purposes and it is already currently available. In spite of those advantages, it is still only a temporary solution. The advantage of 5G based positioning, when it will be finally implemented, is that there is no need for additional, dedicated positioning hardware. The same hardware that offers data connectivity will also offer the positioning solution. 5G positioning will be the method of choice for indoor positioning in the future and is also the focus of the current 5G-TIMBER project. Considering this, it is clear that despite the UWB positioning being a temporary solution, the work on the implementation of 5G positioning must also continue.

It is planned to install at least two Nokia-made base stations, capable of providing the necessary SSB beams, supported by ELISA network operator. The purchase of a R&S 5G scanner will then allow to build a testbed for implementing DL-AOD positioning method. To the knowledge of the authors, such method has not been implemented previously, so it has some novelty in it.

If the necessary hardware and software components will be available later, but still during the project timeline, then also UL-AOA positioning could be implemented. Mentioned availability can either mean FR2 equipment by the project partners, or update of the network provided by the Elisa. There is a reason to believe that UL-AOA method could be more accurate than DL-AOD.

Availability and accuracy of indoor positioning can be improved by using multiple positioning systems simultaneously. More precisely, inputs provided by the UWB positioning system, camera-based positioning system, and experimental 5G positioning testbed. It is reasonable to assume that not all the measurement results of all those systems are accessible for data fusion. Thus, a high-end solution, where inputs are coordinated along with their associated reliability, will be a more practical solution here. Finally, precise position information can help; we use XApps of Open RAN to take advantage of the precise positioning coming from UWB and use that for other purposes including the optimization of the 5G network e.g., handover, interference management etc., as mentioned in D1.8.

Keeping the track of previous locations of the (each) UE can be used to improve accuracy of the current position estimated based on previous history alongside the new measurements.

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