POLITECNICO MILANO 1863

SCUOLA DI INGEGNERIA INDUSTRIALE E DELL'INFORMAZIONE

Executive Summary of the Thesis

Hybrid Vehicular Localization Algorithms using 5G Technology and IMU Sensor

Laurea Magistrale in Automation and Control Engineering - Ingegneria dell'Automazione e del Controllo

Author: Marco Vellucci

Advisor: Prof.ssa Monica Barbara Nicoli

Co-advisor: Prof. Mattia Brambilla, Ing. Marco Piavanini

Academic year: 2021-2022

1. Introduction

During last decade, we experience the increment of the interest in the short-range telecommunications field, in particular in studying the possible applications regarding the connections between vehicles (Vehicle-To-Vehicle (V2V)), or vehicles to infrastructure (Vehicle-To-Infrastructure (V2I)) and vice versa, or again Vehicle-To-Network (V2N) [7]. The conventional Global Navigation Satellite System (GNSS) is the widest used technology in order to retrieve the position information, but despite its largely known appliance it does not guarantee so reliable accuracy for our purposes: the development of automated driving services is constrained by the standard GNSS's performance in terms of precision of localization, which is in the order of meters. The limitations of such technology is really paralyzing in terms of development for most advanced automotive-based applications, because of safety-related implications. Mobile radio-based positioning techniques can be used to get over these restrictions, and the Fifth Generation (5G) cellular technology [2] is anticipated to introduce unique characteristics that could improve the positioning precision.

2. Objectives

The main purpose of this thesis is to propose an algorithm for localization of vehicles, in which Inertial Measurement Unit (IMU) sensor information are considered as additional input for the filter used for prediction. This goal has been pursued passing through a deep analysis of the available instruments and technologies. Then, the Third Generation Partnership Project (3GPP) is considered in order to understand the 5G New Radio standards [3]. The two anchor points of this work are: understanding of the localization problem, and diving deep in the possible enabling technologies, trying to use them in the proposed localization algorithm, in which the will is to merge the advantages of 5G technology and on-board IMU sensor. Essentially, the thesis explores the development of a hybrid localization algorithm based on an Interactive Multiple Model (IMM) [4] suited for the purpose. The contributions of this thesis research can be summarized as follows:

- Design of a localization algorithm based on the hybridization of measurements of different types, such as GNSS, 5G TDoA, calculated as ToA differences, and also an integration of inertial measurements from Inertial Measurement Unit.

- The simulations have been made considering a realistic scenario, in this psecific case it is a circuit, in order to have the possibility of considering all different situations. The simulations take into account the deployment of the orbits of the Global Positioning System (GPS) satellites that make up the Global Navigation Satellite System (GNSS) constellation.
- Results analysis obtained for different technologies.

3. Related works

Before starting with the development of the algorithm, a wide study in literature has been conducted in order to understand what is the state of art, and to take some already developed ideas to improve the algorithm as well. All these researches were about GNSS, 5G Technology and IMU sensors' applications. In this work, one of the most difficult points was the tuning of the parameters of the filter used for tracking, since the Kalman Filter (KF)s require a trial and error procedure to find the best values to use. A tracking filter technique is built with a basic vehicle motion model using 5G and Inertial Measurement Unit (IMU) measurements in [5], which is another work that was crucial in the creation of this study. Last but not least, this evaluation also emphasized the absence of a full strong and comprehensive investigation in the field of vehicular localization, for autonomous driving application, to create a solid foundation for the analysis that was later undertaken. A framework that combines a tracking modeling design for dynamic vehicle localization with a positioning solution that is both full hybrid and takes care of 5G standards is still in development.

4. Scenario and system model

The scenario for all the tests and the data collection used as basis for the implementation and simulation of the proposed algorithm is the race circuit in *Castelletto di Branduzzo*, Pavia.

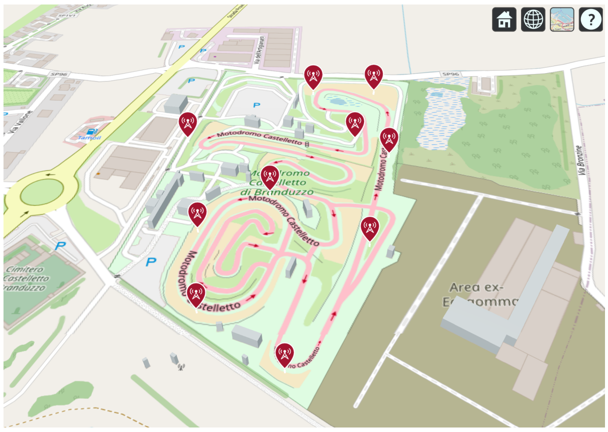

Figure 1: Motordrome scenario and layout of the Base Stations

This racetrack has been evaluated as a good benchmark because of its characteristics: it has all the specifications useful to simulate a real speedway scenario.
The other scenario considered for the evaluation of the proposed algorithm is a real reduced sector of the previously named motordrome:

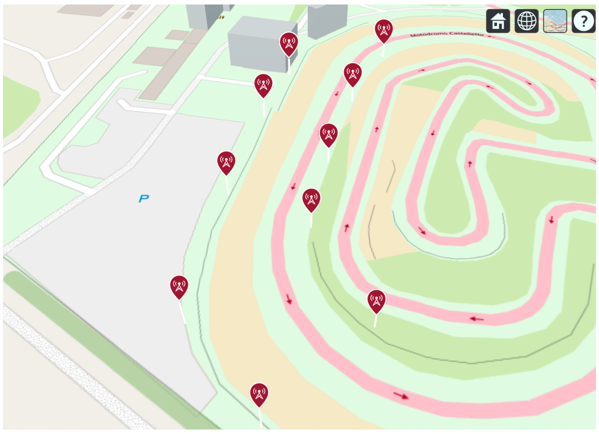

Figure 2: Scenario and layout of the Base Stations

4.1. Design of the scenario

In order to account for the visibility of satellites while determining the positions of the GNSS satellites, we modelled an actual GPS constellation over the region of interest at the time the simulation was run. It has been also considered a so-called elevation mask to consider the height of the buildings influencing the visibility in the GPS constellation. A ray tracer utilizing the Shooting and Bouncing Ray (SBR) method was then used to determine the BSs visibility conditions in each location where the vehicle had to be situated using a 3D model of the environment. The broadcast signal was then created with a specific carrier configuration in terms of numerology (or subcarrier spacing) and Positioning Reference Signal (PRS) properties, in accordance with 5G Orthogonal Frequency Division Multiplexing (OFDM) modulation.

5G and OFDM	
Number of Base Stations	10
Transmitted Power	24 dBm
Frequency	800 MHz
Subcarrier Spacing	120 kHz
Transmission Channel (Raytracer)	
Maximum Number of Reflections	3
Signal to Noise Ratio (SNR)	15
Receiver Sensitivity	-100 dBm

Table 1: Parameters used for simulations.

In order to consider an Inertial Measurement Unit in simulations, it has been characterized by the following parameters:

Accelerometer	
Measurement range	156.96 m/s^2
Scale factor	10^{-3} $(m/s^2)/LSB$
Bias instability	10^-1 m/s^2
Gyroscope	
Measurement range	11.1 rad/s
Scale factor	10^{-3} $(rad/s)/LSB$
Bias instability	$2 \cdot 10^{-2}$ rad/s

Table 2: IMU's parameters used for simulations.

4.2. Motion models and positioning algorithm

The algorithm for localization is based on an Interactive Multiple Model (IMM), obtained as the merging of three different motion models. The considered models are:

- Nearly Constant Velocity (NCV): considers a straight vehicles' trajectory;
- Nearly Constant Acceleration (NCA): to take into account for accelerations and decelerations, characteristics of each typical situation (crossroads, traffic lights);
- Constant Turn Rate (CTR): to account for turning maneuvers with constant turning rates.

To each motion model corresponds an Unscented Kalman Filter [6], custom made for that model, and used to predict the state at the next time step. These filters are then used to make a correction of the prediction, starting from the knowledge of the system and measurement model. The technique behind this filter is the so-called Unscented Transform (UT) that is a deterministic sampling technique to pick a minimal set of sample points (σ-points) around the mean. Essentially, the objective is to find a transformation that can approximate the mean and covariance of a random vector when it is transformed by a non-linear function. The UKF is able to obtain the same estimation of an EKF with accuracy at the third order (Taylor series expansion) if considering Gaussian noises.

5. Results

5.1. Positioning performance

The performance of each filter and technology has to be evaluated in terms of accuracy. The CDF is plotted and evaluated for different values of the CEP. In the following, a plot and a resuming table are reported to give an idea of the performance reached by the created algorithm:

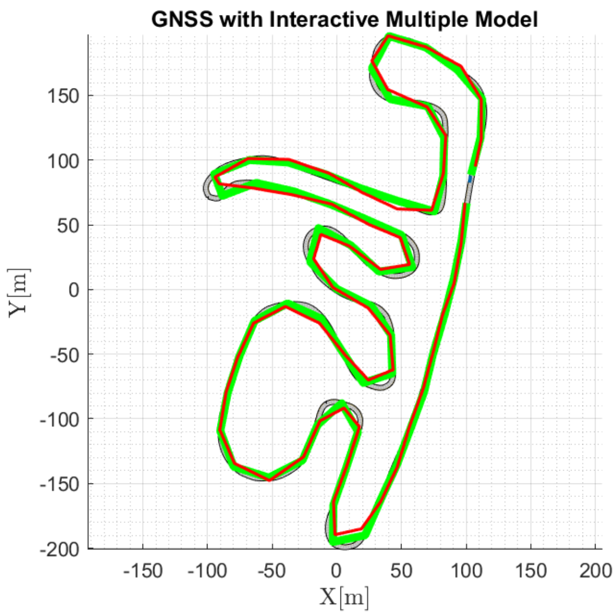

Figure 3: Stand-alone GNSS localization: UKF trajectory prediction (red) vs.Ground Truth (green).

Positioning Accuracy [m]				
Motion Model	50%	60%	80%	95%
IMM	1.89	2.37	3.32	6.72
NCA	3.17	3.65	4.92	7.88
NCV	8.72	12.93	14.02	16.5
CTR	7.25	9.61	14.33	27.81

Table 3: Positioning accuracy in stand-alone GNSS localization (Figure 3).

The IMM method, which takes into account all four motion models, consistently beats all other Kalman Filters. This is because the IMM reduces positioning error during maneuvers, whereas the previous single models are not appropriate for capturing both maneuvers and non-maneuvers dynamics simultaneously. The position error of the individual motion models is strongly dependent on the characteristics of the motion models themselves, demonstrating the importance of carefully considering the models to be implemented with the IMM.

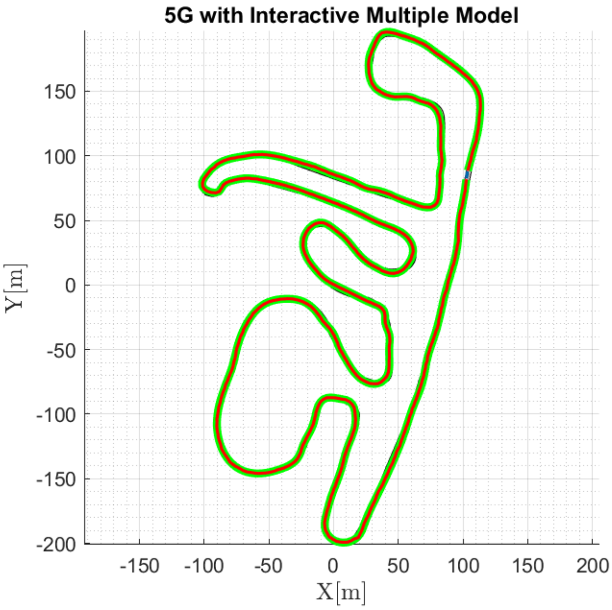

Figure 4: 5G localization: UKF trajectory prediction (red) vs. Ground Truth (green).

Positioning Accuracy [m]				
Motion Model	50%	60%	80%	95%
IMM	0.15	0.17	0.22	0.39
NCA	0.16	0.19	0.27	0.49
NCV	0.34	0.43	0.46	1.38
CTR	0.21	0.25	0.68	1.04

Table 4: Positioning accuracy in stand-alone 5G localization (Figure 4).

From the Table 4 it can be seen that the IMM easily have better performance with respect to the single motion models. The localization with 5G technology is characterized by a maximum error, in the 95% of the cases, equal to 39 cm with such a filter as method of prediction.

Another scenario taken into consideration to validate the proposed algorithm for 5G localization is a real reduced sector of the previously considered motordrome, that has the following results:

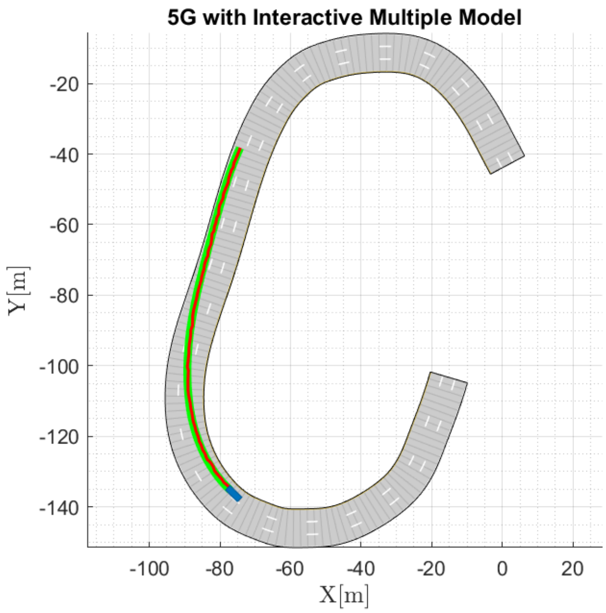

Figure 5: 5G localization: UKF trajectory prediction (red) vs. Ground Truth (green).

Positioning Accuracy [m]				
Motion Model	50%	60%	80%	95%
IMM	0.236	0.258	0.33	0.43

Table 5: Summary table of the results in Figure 5.

An interesting result is the one that can be seen in the following Table 6, showing the localization with 5G technology, plus the information from an IMU sensor, for the same real reduced sector of the motordrome:

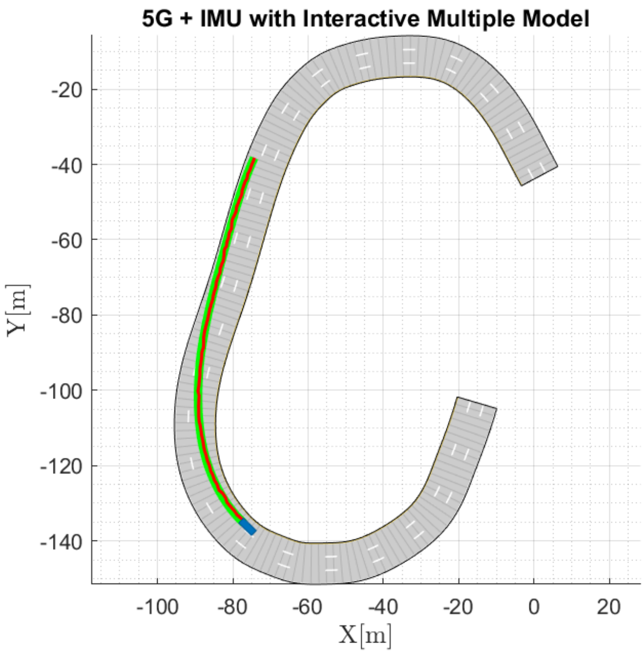

Figure 6: Hybrid 5G/IMU localization: UKF trajectory prediction (red) vs. Ground Truth (green). Same scenario of Figure 5

Positioning Accuracy [m]				
Technology	50%	60%	80%	95%
5G	0.236	0.258	0.33	0.43
5G/IMU	0.233	0.255	0.33	0.43

Table 6: Comparison between performance of 5G and 5G/IMU in a real reduced sector of the motordrome in Figure 6.

It is visible from the just shown graphics that the hybridization of 5G and IMU is able to obtain results comparable to the 5G, and this may be due to parameters' tuning reasons. However, these results are good considering that they are strongly dependent also on the quality of the sensor used, in terms of scale factor, measurement noise, and constant error [1].

6. Conclusions and future works

This thesis had the aim to develop different types of localization algorithms for real vehicular applications, trying to build a final localization algorithm that is able to obtain good performance in terms of accuracy and precision for a future real application. The hybridization of 5G and IMU is able to obtain results comparable to 5G, and this may be due to parameters' tuning reasons. However, it can be assessed that this work can be a good starting point for a future development, with a specific attention to the last part, so the localization using 5G technology and IMU. The contribution of cheap sensors, like IMU, placed on the vehicle can be an additional value only if control systems onboard will be able to manage and correct all the errors due to different noisy components IMU sensors suffers of. Another point to highlight is that in this thesis it has been considered a 2D localization, whereas for future real application the requirement will be a 3D precise localization probably. The algorithm already contemplates the passage from 2D to 3D localization thanks to the fact that all the code is developed with an almost total parametrization of the functions. It is not the aim of this thesis to analyze the performance in this scenario, but the flexibility of the code is anyway good point.
For future works, some points can be highlighted and summarized here below:

- An adaptive Kalman Filter can be developed and put into action, in order to consider the different sources of instability present in the real scenario, in different manoeuvres;
- More advanced data fusion filters, such as particle filters, can be implemented instead of the Unscented Kalman Filter to get closer to applicability.

It is important to underline that the obtained results could be really interesting and encouraging because not a straight and uncomplicated highway is evaluated, but the algorithm has been tested on scenarios taking into account for all possible common manoeuvres of a real driving situation.

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Hybrid Vehicular Localization Algorithms using 5G Technology and IMU Sensor

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Author: **Marco Vellucci**

Student ID: 964744
Advisor: Prof.ssa Monica Barbara Nicoli
Co-advisors: Prof. Mattia Brambilla, Ing. Marco Piavanini
Academic Year: 2021-2022

Abstract

The interest in the field of telecommunications has increased over the past ten years, particularly in exploring potential applications involving connections between vehicles (V2V), or vehicles to everything (V2X), and vice versa. This interest results in increased R&D process spending in this field. Because of the desire to create a logistic system that is ever more efficient, dynamic, and secure, this kind of connections are being studied so much. In reality, it is obvious that advancements in telecommunications play a crucial part in forging such an atmosphere. By clearly referring to pedestrians, infrastructure, roads, and cars, I mean all the actors involved, the deployment of these solutions might enable the sharing of a great deal of information through all of them. The widespread Global Navigation Satellite System (GNSS) technology might not be able to provide positioning solutions that are up to the challenging requirements, which might allow wireless positioning techniques based on Fifth Generation (5G) cellular networks to play a promising role in positioning systems.

This work proposes a novel localization algorithm based on the fusion of different available technologies in order to obtain a certain precision in localizing vehicles. The hybridization between GNSS, 5G TDoA (Time Difference of Arrival) and IMU sensor is used to obtain the vehicle's position estimates, thanks to a fitted for purpose tracking filter, considering an Interactive Multiple Model (IMM). Essentially, the aim is to realize a hybrid integration of the 5G network architecture, based on actual base station installation sites, with the visibility of GNSS satellites in a particular geographic area. The Line-Of-Sight (LOS) conditions of the accessible satellites and cellular links are established by utilizing a three-dimensional (3D) city map of the area, employing an elevation mask and a ray tracing based method, after producing a realistic dynamic trajectory for the vehicle.

Keywords: 5G, Positioning system, Hybrid localization, Interactive Multiple Model, Kalman Filter, IMU

Abstract in lingua italiana

L'interesse nel campo delle telecomunicazioni è cresciuto nell'ultimo decennio, in particolare nell'esplorare le potenziali applicazioni che coinvolgono le connessioni tra veicoli (V2V), o veicoli a tutto, e viceversa. Questo interesse si traduce in un aumento degli investimenti di ricerca e sviluppo in questo settore. A causa del desiderio di creare un sistema logistico sempre più efficiente, dinamico e sicuro, questi tipi di connessioni sono molto studiati. Ovviamente i progressi nelle telecomunicazioni svolgono un ruolo cruciale nella creazione di tale panorama. Riferendosi chiaramente ai pedoni, alle infrastrutture, alle strade e alle automobili, ovvero tutti gli attori coinvolti, la distribuzione di queste soluzioni potrebbe consentire la condivisione di una grande quantità di informazioni attraverso tutti loro. La diffusa tecnologia GNSS potrebbe non essere in grado di fornire soluzioni di posizionamento che soddisfino i requisiti alquanto impegnativi, il che potrebbe consentire alle tecniche di localizzazione wireless basate sulle reti cellulari 5G (Quinta Generazione) di svolgere un ruolo promettente nei sistemi di posizionamento.

Questo lavoro di tesi propone un nuovo algoritmo di localizzazione basato sulla fusione di diverse tecnologie disponibili al fine di ottenere una certa precisione nel localizzare i veicoli. L'ibridizzazione tra GNSS, 5G TDoA (Time Difference of Arrival) e sensore IMU viene utilizzata per ottenere le stime di posizione del veicolo, grazie a un filtro di tracciamento creato per lo scopo, considerando un Modello Multiplo Interattivo (IMM). In sostanza, l'obiettivo è realizzare un'integrazione ibrida dell'architettura di rete 5G, basata sui siti di installazione delle stazioni di base reali, con la visibilità dei satelliti GNSS in una particolare area geografica. Le condizioni di Line-Of-Sight (LOS) dei satelliti accessibili e dei collegamenti cellulari sono stabilite utilizzando una mappa tridimensionale (3D) della zona, impiegando una maschera di altitudine (elevation mask) e un metodo basato sul raggio di tracciamento (ray tracing), dopo aver prodotto una traiettoria dinamica realistica per il veicolo.

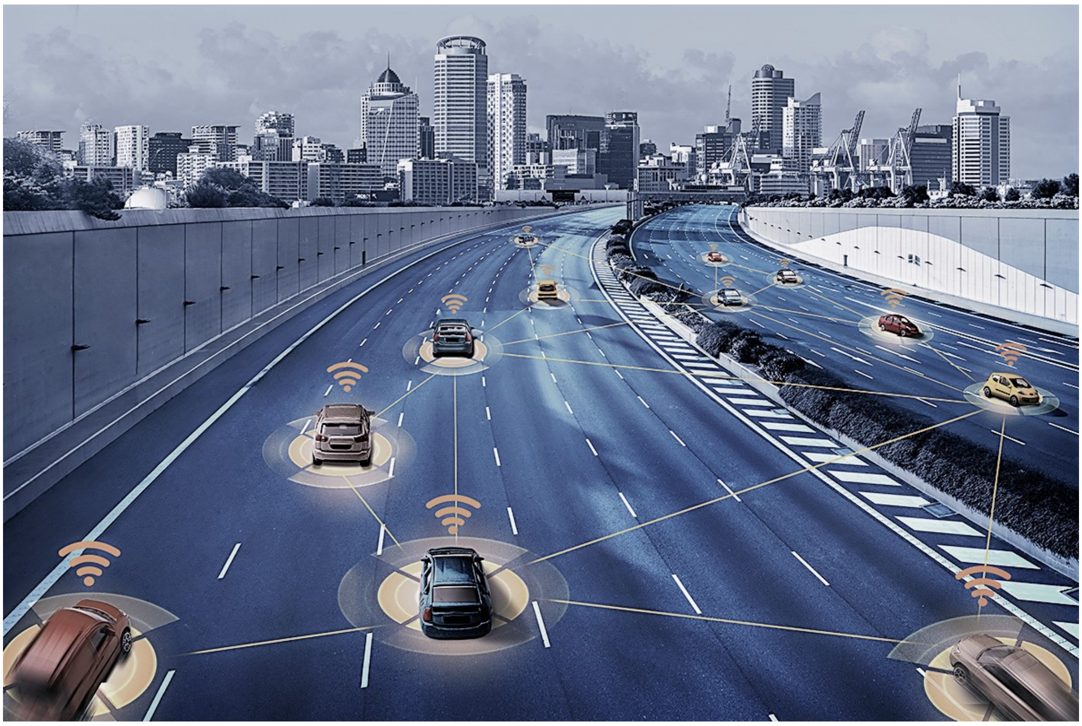
Parole chiave: 5G, Sistemi di posizionamento, Localizzazione ibrida, Modello di Moto Interattivo, Filtro di Kalman, IMU

Contents

Introduction

0.1. Overview

During last decade, we experience the increment of the interest in the telecommunications field, in particular in studying the possible applications regarding the connections between vehicles (V2V), or vehicles to infrastructure (V2I) and vice versa, or again vehicle to network (V2N). This interest translates in more investments for Research and Development (RD) process inheriting this field. This kind of connections is being investigated so much because of the volition to build a logistic system more and more efficient, dynamic and safe. The implementation of these solutions might allow to share lots of information through all the actors involved: clearly referring to pedestrians, infrastructures, roads and vehicles. To obtain the desired amount of information between them, we must consider the newest technological resources, in particular the last cellular connection technology 5G NR [17] [3].



This thesis wants to explore is the one involving the autonomous vehicles, and so smart-roads ad smart-infrastructures. And the most important information from which automated driving and V2X services take advantage of is the position [9]. There are lots of techniques and technologies in the scientific literature for this purpose, but their application strictly depends on the environmental scenario, such as [15] [12]. The conventional GNSS is the widest used technology in order to retrieve the position information, but despite its largely known appliance it does not guarantee so reliable accuracy for our purposes: the development of automated driving services is constrained by the standard GNSS's possible precision, which is in the order of meters. A huge amount of different solutions to improve the performance of GNSS standard is available in the literature. Real Time Kinematic (RTK) solutions can be used to increase accuracy; an RTK base station equipped with a radio antenna and a GNSS antenna whose positions are known computes and transmits differential real-time corrections data via the radio link to enable the Global Positioning System (GPS) system to correct its position. Other Augmented Global Navigation Satellite System (A-GNSS) methods like the Assisted Global Positioning System (A-GPS) and Differential Global Positioning System (D-GPS) can also increase the accuracy of positioning estimation. The first one improves startup performance by sending the receiver startup data—used to establish the connection—via a radio network interface rather than a satellite link. By transmitting positional corrections to receiver base stations, a fixed network of base reference stations in D-GPS supports the pseudorange estimation.

Positioning and localization using a wireless technology rely on different elements, such as received power, range or angle-based measurements. The accuracy of those systems is affected by several known factors, depending on the technology used.

The basic idea underlying the working principle of the GNSS is basically the same as the so-called time-of-flight sensors. We use electromagnetic waves to measure the distance from the satellite to the user (referring to as UE) and, once we calculate enough distances between them and we know the satellite constellation at the time of the measurements, we can reconstruct UE position through a simple triangulation. To perform a good estimation we need to take into account for errors and their sources, and it's well known that these are [8]:

1. Ionospheric delays: the ionosphere contains electrically charged particles called ions which delays the satellite signals;

2. Tropospheric delays: are caused by humidity, temperature and atmospheric pressure in the troposphere;

3. Orbit errors: GNSS satellites travel in very precise, well-known orbits. However,

the orbits vary a small amount;

4. Satellite clock errors: the atomic clocks in the GNSS are very accurate, but they drift a small amount;

5. Multipath: it occurs when GNSS signal is reflected off an object, such as the wall of a building , to the GNSS antenna. The reflected signal arrives at the receiver slightly delayed. The error caused by multipath it's a non-negligible factor because it influences a lot the positioning estimation;

6. Receiver noise: receivers, especially the cheap ones, have some clock error due to hardware and/or software errors.

As mentioned in the overview section, we have several methods to improve performance of GNSS and they are briefly explained in the following.

- Multi-frequency: devices capable of receiving GNSS signals of two or more frequencies, can observe and correct frequency-dependent errors, such as ionospheric delays and tropospheric delays;

- Multi-constellation: devices capable of receiving GNSS signals from different constellations can improve coverage, reduce errors caused by obstruction and solve for range with higher accuracy;

- Differential Global Navigation Satellite System (D-GNSS): a fixed GNSS receiver (base station) is placed at a known position. The base station computes the error between the known and measured position. Through a data link (radio or internet), the base station sends these errors to the other receivers (rovers). Errors are mostly attributed to atmospheric delay, orbit errors and clock errors. If the rover is within few kilometres, D-GNSS works very well since the atmospheric conditions are similar;

- Real Time Kinematic (RTK): it has the same structure of D-GNSS but uses a carrier-based method for range computation.

More widespread solutions are explained in the following:

- Satellite-Based Augmentation System (SBAS): these systems are geosynchronous satellite systems that provide regional services for improving the integrity, accuracy, and availability of basic GNSS signals. Receivers in some Reference Stations estimate satellite's time and orbit errors among with ionospheric delays. Corrections are sent to SBAS satellites by the Uplink Stations.

- Precise Point Positioning (PPP): it has the same structure of SBAS but use carrier-based method for range computation.

So we can say that the RTK method can give measurements accurate to the centimeter level in open areas, improving by an order of magnitude the performance of the classic GPS-only localization, and it allows also a global localization. The problem of the RTK-GPS localization method is that it performs badly close to buildings, so in general in urban areas, and that accuracy, availability, integrity and continuity are hard and expensive to guarantee.
These are some of the so-called Key Performance Indicator (KPI)s to be considered for the performance evaluation of all the localization techniques explored in this work, and the most common ones are: availabilty, reliability, update rate, position accuracy. The last one is also the most significant one, simply because it provides a clear idea of the applicability of a method in a urban environment, that is our final aim.

It is not easy to satisfy the challenging requirements using only one of the previous listed techniques, because the advanced V2X use cases and services of our interest require high positioning performance: the accuracy requirement is $30cm$ in 95% of cases (CEP). In order to go over these limitations, it is useful to consider cellular mobile radio-based positioning methods, since in the last decades the development of cellular mobile radio signals improved a lot: from the Second Generation (2G) to the 4G-LTE. These developments was focused on improving the quality of the services for the final user, so the consumer. Nowadays the upgrading in this field is leading to a new era, in fact the 5G technology was not meant only for common services: increased bandwidth and connectivity speeds will bring great benefits to industries, which will see the full implementation of smart factories, i.e. smart plants, where production facilities will be fully automated. With the entry of 5G in the factories, the prospect is the transformation of the entire production sphere through the convergence of digital and internet technologies with the traditional industry, merging Operational Technology (OT) and Information Technology (IT) into a common system that allows the complete digitalization of business and production processes [1]. Location-based services promise to represent a massive market chance for both operators and customers.

0.2. Inertial Navigation Systems

The Inertial Navigation System (INS) consists of a set of sensors, including accelerometers and gyroscopes, which allow measurements of acceleration and angular velocity compared to an inertial reference system, such as, within limited periods of time, the Earth Centered

Inertial (ECI) system, which has its origin in the center of the Earth, the x axis facing the gamma point of the constellation of the Aries, the z axis parallel to the axis of rotation, and the y axis accordingly to obtain a right-handed triad [2].

These measurements are then used for various purposes, such as to estimate location, speed and layout through specific equations implemented by a calculator that collects the data. The advantage of these sensors is that they provide measurements without exploiting external references or signals, as is the case with GPS; however, they present various types of errors that prevent their prolonged use without the appropriate corrections. The measurements that these sensors provide are affected by different types of errors, and it is important to know their nature to understand how to compensate their influence when using the measured sizes to make calculations. First, it is important to distinguish between these two categories:

- Deterministic errors: are due to constructive aspects, also related to the technology used and the operating temperature of the sensor.
- Stochastic errors: are noises related to random processes.

To get into more detail, we distinguish between scale factor, white noise and constant error (bias or drift):

- Scale factor: it is essentially a relationship between the input and the output of the sensor, so to obtain the correct measurement it is necessary to compensate by multiplying by a certain factor (or matrix in case of a vectorial measurement). This type of noise is most influential in the case of sudden accelerations or rotations.
- White noise: it varies much faster than the sensor sampling period (it works at higher frequencies). It can be thought of as a very rapid sequence of random values without any correlation between them, with null average and distributed with variance σ^2.
- Constant error (bias or drift): it is called bias in the case of accelerometers and drift for gyroscopes, and represents the average value of the sensor output when the accelerometer (or gyroscope) is actually standing (with zero angle speed). This is mainly due to structural defects.

0.3. Thesis Structure

The following structure for the thesis can be used:

- Chapter 1: from a theoretical standpoint, this chapter provides an overview of the key ideas. The description starts off by highlighting the key components of the general localization problem before concentrating on the various types of measurements. An overview on the enabling technologies for localization, and specifically on the ones used for the thesis' development is exposed. Finally, a summary of the 5G NR positioning techniques, including Positioning Reference Signal (PRS) and frame structure, is provided.
- Chapter 2: it is focused on the explanation of the motion models considered for the design and implementation of the tracking algorithms.
- Chapter 3: in the first part there is a technical explanation of the most known filters used for localization purposes. Then, the choices to design and implement the tracking algorithms and the introduction to the Interactive Multiple Model (IMM) are provided.
- Chapter 4: it focuses on the description of the scenario details considered for the algorithm testing and the characteristics of the different types of localization performed.
- Chapter 5: this thesis is concluded by making a few noteworthy points about the entire endeavor, as well as outlining the biggest difficulties we encountered and making some suggestions for potential future works and research.

1 | Basics of localization

This chapter wants to give to the reader some basics of localization in order to provide a better understanding of the problem under study and some useful information to perform a more critical analysis of the content. A first explanation about localization estimation and tracking filters to perform position estimation are also present, with an overview on 5G NR positioning methods and their frame structure.

1.1. The localization problem

Trajectory tracking for future autonomous vehicles is one of the most important arguments, in fact we can usually divide the autonomous driving stuck in three parts: *perception, planning* and *control*. Perception and control are the interfaces of our software with the external world, whereas planning can be seen as the core of the software. We can see the different elements of these three parts in the scheme below.

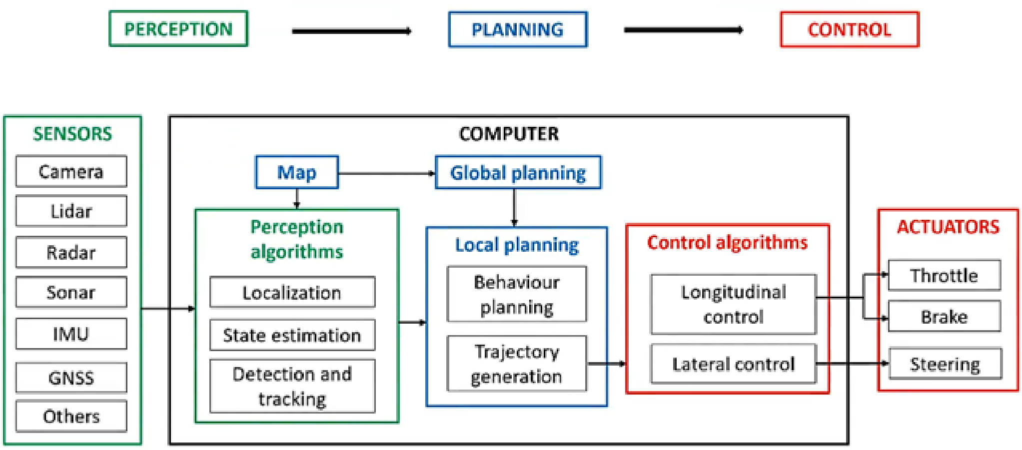


Figure 1.1

The focus of this thesis is on the perception algorithms, so on localization, state estimation and detection and tracking. The enabling technologies for this purpose are represented by different types of sensors and consequent measurements that are available. A fundamental element needed is a set of parameters that allows to put in relation the UE spatial

information with some reference points, with known positions (angles, distances, distance differences,...). The measurements I just mentioned, that are the key parameters for the development of localization algorithms, can be of different nature: they depends on the type of technique has been used for obtaining them. The principal methods used in this research project are angle-based method and range-based method, but also some received power measurements could be used in order to provide the information necessary for the development of tracking algorithms. Correspondingly to the method used for the purpose, multi-angulation or multi-lateration is exploited, based on analytical models to express the geometric relation of the parameters to the location and invert the system.
For localization through GPS technology only range-based parameters are used, whereas considering cellular networks both range-based measurements and angle-based measurements can be taken in consideration. Probably, a good idea is to take into account for both the technologies, because a hybrid localization algorithm can provide more accurate positioning performance. In this thesis the objective is to go through an analysis of three different technologies and their hybridization in order to obtain the best match between them.
In positioning we can underline the main importance of another parameter, that is to say the reference system:

- Cartesian coordinate system: identifying each point in the space by a vector [x,y,z];
- Ellipsoidal reference system: identifying each point in the space with latitude, longitude and altitude/height;
- Descriptive system: partitioning the spatial environment in areas with associated identifiers (cell id, room numbers, floors).

It's also necessary a distributed infrastructure composed by targets, reference stations, control units, servers, and so forth, that implements the positioning process, and its protocols applied between the infrastructure components for coordinating the positioning process.

Now we can use the previously explained parameters in order to formulate the localization problem, simply through an equation:

$$\rho_i = h_i(u(t), s_i) + n_i; \quad i = 1, ..., N \tag{1.1}$$

where $s_i = [s_{ix}, s_{iy}, s_{iz}]$ is the position of the i-th reference station, $u(t)$ is the UE location at time t, and ρ_i is the i-th measurement. The equation expresses the measurement as a function of UE location, and position of the reference station through a deterministic model $h_i(\cdot)$ that is usually non-linear, with the additive stochastic term n_i that accounts for measurement errors over the i-th radio link, due to noise, interference, and other propagation-related problems. The noise creates uncertainty over the location estimation, and it is assumed to be independent between different ρ_i. For N measurements, the maximum value of the i subscript, we get the non-linear system:

$$\begin{bmatrix} \rho_1 \\ \rho_2 \\ \vdots \\ \rho_N \end{bmatrix} = \begin{bmatrix} h_1(\mathbf{u}, s_1) \\ h_2(\mathbf{u}, s_2) \\ \vdots \\ h_N(\mathbf{u}, s_N) \end{bmatrix} + \begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_N \end{bmatrix}$$

whose solution yields the location estimate.

In the following, an overview of the main measurement categories will be provided.

1.2. The potential of 5G

It has to be underlined that 5G is the new technology that will support the increasing rising in the IoT services. The characteristics seen so far as speed and latency allow almost simultaneous connections between remote devices. Furthermore, the possibility of creating low energy consumption mobile telephone repeaters allows to serve even remote areas which have not been connected to broadband networks until now. It goes without saying that the large industrial complexes that are usually located in peripheral or even agricultural areas so far poorly served will benefit from it. This newest technology is leading all network operators to invest in it, and to bet on new business opportunities. In last years it is noticeable the increasing interest in positioning techniques, because high precision positioning services can benefit to different sectors (industry, transport, etc.), in particular in applications like environmental monitoring, smart cities, autonomous vehicles, V2V communications, augmented reality, which need large data transmission capacity.
During past few years 5G wireless systems have received an increasing consensus for their application in three generic services: Enhanced Mobile Broadband (eMBB), Massive Machine Type Communication (mMTC) and Ultra Reliable and Low Latency Communications (URLLC) (also referred to as mission-critical communications) [14]. These three services are characterized by different usage scenarios:

- **eMBB**: to cover densely populated urban centers with downlink speed close to $1Gbps$ *indoor* and $300Mbps$ *outdoor*. Furthermore, it supports stable connections with very high peak data rates; as well as moderate rates for cell-edge users
- **mMTC**: 5G allows a 1000x increment of devices connected to the network. It

also supports a massive number of Internet of Things (IoT) devices, which are only sporadically active and send small data payloads;

- **URLLC**: for critical communications where bandwidth is not as important with respect to reliability and delay - in particular, applications with end-to-end latency of $1ms$ or less. URLLC supports low-latency transmissions of small payloads with very high reliability from a limited set of terminals, which are active according to patterns typically specified by outside events, such as alarms.

1.3. 5G in localization: related strategies

In principle, considering a wireless environment, every kind of propagating signal can give position-dependent information. For this reason, they can be used for localization measuring some signal metrics. In this sense we can individuate metrics such as phase, Received Signal Strength (RSS), Time of Arrival (ToA) and Angle of Arrival (AoA) [6]. It can be also exploited a combination of them, for sure, resulting in a more precise and reliable method of localization. The base of localization algorithms is the presence of one or multiple receivers with one or multiple reference transmitters, that can be of different types: navigation satellites, cellular base stations (BSs) and, for cooperative localization, other mobile users. We can have classify the positioning methods in two general classes:

- Mobile-based: the (mobile) device itself calculates its location by using signal measurements from terrestrial or/and satellite transmitters. The assistance data from the network can be exploited to perform the signal measurements and infer the position;
- Network-based: the network location server infers the position of the mobile device, by means of signal measurements performed by the network with respect to the mobile device, or signal measurements performed and sent by the mobile device to the network.

A classification of the signal processing techniques for cellular networks can be done, but the only one that will be of our interest for our use case is the *trilateration*. Trilateration leads to a position estimation obtained from the intersection of geometric forms (circles, hyperbolas, etc.), created by distance or angle measurements between the terminal and the reference transmitters or receivers. For this type of localization technique, the previously mentioned types of measurements can be used, so Time of Arrival (ToA), Direction of Arrival (DoA) and Received Signal Strength (RSS).

Others signal processing techniques are *proximity* and *fingerprinting*. The first one is base of the fact that the known transmitter position is assigned to be the position of the terminal, and an example can be the *cell-ID* method; the second one is an algorithm based on finding the best match for a certain signal measurement, such as RSS, time delay or channel delay spread, from a database of fingerprints, where each fingerprint is associated to a specific location.

1.3.1. Standardization of 5G

The only GNSS technology is not sufficient for ensuring to satisfy all the requirements for the entire field of use cases in terms of accuracy, availability and integrity for what concerns the most advanced Intelligent Transportation System (ITS) services. 5G technology is the one that can be a good solution to overcome these limitations, and in last years there was being a big push towards the standardisation. A general description of Location Services and corresponding requirements is available thanks to the Third Generation Partnership Project (3GPP), that in last years released different versions of the 5G technology, with a well-structured documentation about technical specifications and most recent use cases. There has been the passage from the Release 15 to the Release 17, and the completion of the last one marks the conclusion of the first phase of the 5G technology evolution. Release 17 delivers another performance boost to the 5G system and continues expanding 5G into new devices, applications, and deployments. It brings further enhancements to the foundational aspects of the 5G system, pushing the technology boundaries on many fronts, including capacity, coverage, latency, power, mobility, and more. We can give a quick understanding in the following:

- Massive Multiple-Input Multiple-Output (MIMO): it is also known as Large Antenna Systems, and it allows you to use two or more transmitters and receivers simultaneously to exchange data on the same radio channel. It will provide also high angular resolution that can be use for angle-based localization;
- Coverage: for deployments in sub-7 GHz, mmWave, and non-terrestrial networks, Release 17 introduced various enhancements to the uplink control and data channel design;
- Spectrum expansion: to scale the existing 5G NR design to expand mmWave spectrum range from 24.25—52.6 GHz up to 71 GHz, also known as FR2-2 band in 3GPP. It includes the support for the global 60 GHz unlicensed band, which can open doors to new use cases and deployments.

In order to provide a localization algorithm with high accuracy performance it's useful to consider also suitable tracking algorithms. For this reason, in the development of the research project the IMM tracking filter is taken into consideration. This filter is able to combine different vehicular dynamics, so that the description of the motion is as accurate as possible. Highly valuable candidate filter to be used for the final IMM are the UKFs, because they are based on non-linear models so that errors coming from the linearization process are avoided [19].

To implement the system and assess its performances, the MatLab Software is used.

1.4. Satellite-based method

As already said before, the most famous system for the satellite-based localization is GPS, that stand for Global Positioning System. It's quite an old technology that was born in 1970 at US Department of Defence. Its initially scope was to satisfy the need of localizing military vehicles on the Earth and space. Even if GPS was used only for military purposes, it was developed to be scalable, so satellites were thought to serve a non-specified number of users (forward thinking: it was ready to serve a larger number of users than ones it was actually serving). This kind of systems is composed by three fundamental entities: geostationary satellites, receivers of the radio signals and control stations that monitor the satellite state. In the next, GNSS is the name which will be used referring to satellite system because it's the most general term.

The aim of this section is to proved a general view of the principles of GNSS, since its technology was already widely studied in lots of researches and our final purpose is not to provide a further development in these terms.

The idea of GNSS positioning technology is basically to use some wave measuring the distance from the satellites to the user and, once we know enough distances between them and we know where the satellites are, we can reconstruct UE position through a simple triangulation. The control stations have the task to keep the satellite and receiver clocks synchronized, so that we can use them to compare the time at which a given signal is received to the time it was sent. For each satellite, the receiver recovers the information that was transmitted and the time of transmission to determine the propagation time (Δt). The range between receiver and a satellite is obtained as:

$$d = c \cdot \Delta t = c \cdot (t_{receiver} - t_{satellite}) \tag{1.2}$$

In satellite-based method for positioning, the UE location is estimated by using ToA measurements from a certain number of LOS satellites. In theory, the 3D position x, y, z

computed from 3 range measurements plus the knowledge of being on the Earth's surface. Since the receiver's clock is not accurate enough (a time offset of $1\mu s$ causes a range error of $300m$), its time offset is added to the estimated states x, y, z, t_offset. The general GNSS pseudo-range from the i-th satellite s_i under the assumption of LOS condition can be expressed as:

$$\hat{\rho}_i^{(GNSS)} = c \cdot \hat{\tau}_i^{(GNSS)} = ||s_i - \mathbf{u}||_2 + c \cdot \delta t + e_i = h_i(s_i, \mathbf{u}, c \cdot \delta t) + e_i \tag{1.3}$$

being $\hat{\tau}_i^{(GNSS)}$ the estimated ToA of the i-th GNSS satellite signal, δt the clock offset of the UE with respect to a GNSS reference time and e_i the pseudo-range error. The last term includes also the errors deriving from different sources, here re-called for clarity, such as ionospheric and tropospheric delays, multipath phenomenon and receiver noise.

1.5. Range-based method

Range-based measurements working principle is based on the calculation of the distances between the UE location and the reference stations. This kind of method is possible to be applied if and only if the signal sent by the transmitter has the information about time inside it. In fact, knowing this parameter the Time of Arrival (ToA) of the signal can be easily calculated. Essentially we can define the ToA as the difference between the RX time (measured) and the TX time (known, e.g. included in the payload) of the pilot signal:

$$\tau = t_r - t_s \tag{1.4}$$

Then the distance is obtained as:

$$d = c \cdot \tau \tag{1.5}$$

The two time instants, t_r and t_s, must be referred to the same timing system, so it's important the clock synchronization between terminal and all reference stations (completely synchronized network). The measured range $\hat{\tau} = \tau + \Delta\tau$ is affected by error $\Delta\tau$ due to non-perfect synchronization and finite resolution of t_r measurement, and the pseudo-range (used instead of range because of the presence of noise) is given by the equation:

$$\hat{\rho}_i^{(ToA)} = c \cdot \hat{\tau}_i^{(ToA)} = c \cdot (\tau_i + \Delta\tau_i) = d_i + n_i = ||s_i - \mathbf{u}||_2 + n_i \tag{1.6}$$

To keep the stations synchronized among each other, time offset, drift, and drift rate (i.e., the rate of variation of the frequency offset) are measured w.r.t. a common timing system and compensated. If the clock terminal is not synchronized to the common timing system, one of the possible solutions to be employed is to use the two-way (or round-trip) ToA measurements, in which transmission and reception times are observed at the same terminal avoiding any impact of the clock offset between the two terminals. In this case the pseudo-range is given by:

$$\hat{\rho}_i^{(RTT)} = c \cdot \hat{\tau}_i^{(RTT)} = c \cdot (2 \cdot \hat{\tau}_i + \tau_{reply}) \tag{1.7}$$

where τ_{reply} is the time needed by the UE to send the signal back again to the chosen terminal.

Another solution is to use the so-called Time Difference of Arrival (TDoA): the only difference with the classical ToA is that in this case ToA differences between two reference stations are used. The good new with this solution is that the user terminal does not need to be synchronized to the reference stations: synchronization is required only at the reference stations. The pseudo-range for TDoA solution is given by the equation below:

$$\hat{\rho}_{i,j}^{(TDoA)} = c \cdot \hat{\tau}_{i,j}^{(TDoA)} = d_{i,j} + n_{i,j} = ||s_i - \mathbf{u}||_2 - ||s_j - \mathbf{u}||_2 + n_{i,j}, \qquad i \neq j \tag{1.8}$$

Essentially, TDoA can be estimated as difference of ToA estimates, with accuracy limit depending on effective bandwidth and SNR. So, this kind of solutions for range-based measurements can provide high location accuracy, because the higher the bandwidth the better the ToA estimation. Obviously, this performance is reached in case of line-of-sight (LOS) propagation of the signal, absence of obstructions and multipath, because all these disturbances strongly affect the accuracy of the measurement, reducing it significantly.

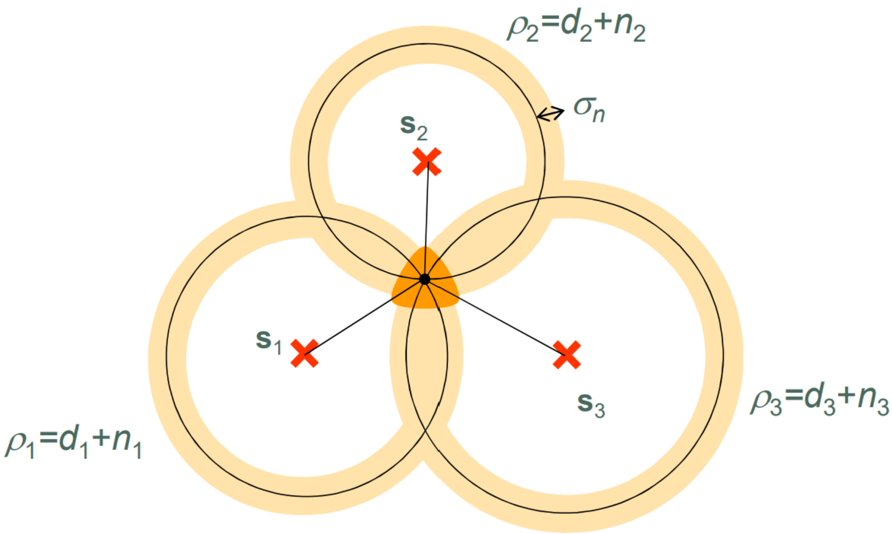


Figure 1.2: Circular multi-lateration problem of locating a UE with range-based ToA measurements. In this situation, it is necessary to use at least three separate BSs, each of which should draw an imaginary circle.

1.6. Angle-based method

The second main method used to calculate the location of a target, referring to as UE in this research project, is the one based on the measurement of the Angle of Arrival (AoA).

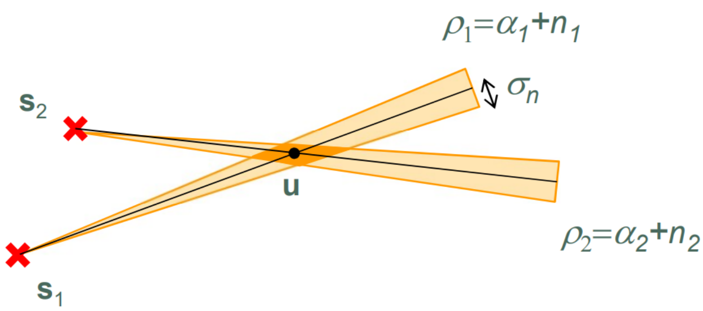


Figure 1.3: Multi-angulation problem locating a UE with angle-based AoA measurements. In this case, at least two BSs have to be used.

The image above is the representation of the angle of arrival, that can be defined with the following expression:

$$\alpha = \arctan \frac{u_y - s_y}{u_x - s_x} \tag{1.9}$$

An AoA measurement provides the angle between the UE and the reference point, a BS in our case, assuming that the BS is providing angle-based information, and the expression for the pseudo-angle in this case is:

$$\hat{\alpha}_i = \alpha_i + n_i = \arctan(\frac{u_y - s_{iy}}{u_x - s_{ix}}) + n_i \tag{1.10}$$

in which the non-linear function $h(\cdot)$ is represented by $h(u) = \arctan(\frac{u_y - s_{iy}}{u_x - s_{ix}})$ whereas n_i accounts for the noise term.

The main sources of error for the angle-based method are noise, fading, multipath, NLOS (non-line-of-sigth) and imperfect antenna array calibration. Commonly, multiple antennas in the form of an antenna array are employed at a node in order to estimate the AOA of the signal arriving at that node, as it can be seen in the image below.

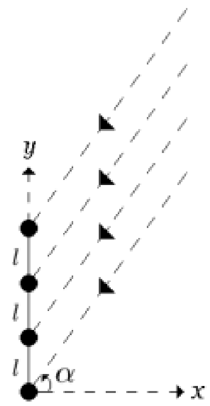


Figure 1.4

The main idea behind AOA estimation via antenna arrays is that differences in arrival times of an incoming signal at different antenna elements contain the angle information for a known array geometry.
For AoA estimation, two methods can be individuated:

- Beamforming: it consists in the combination of phase-shifted versions of received signals at array elements. Weights used for combination are chosen so as to maximize the power received from a given angle. The AoA is estimated by performing beamforming for various angles and finding the one that maximizes the received power;
- Maximum Likelihood algorithms: high resolution AoA estimation can e obtained using this kind of algorithms;

- Subspace-based methods: they can account for multipath propagation, and example of these methods are ESPRIT or MUSIC.

It can be observed [?] that the accuracy of AOA estimation increases, as SNR, effective bandwidth, the number of antenna elements and/or inter-element spacing are increased. In particular, it's important to underline that the accuracy of an AoA estimate increases linearly with the effective bandwidth, which implies that Ultra WideBand (UWB) signals can facilitate high-precision AoA estimation.

1.7. Positioning Reference Signals

A lot of material has previously been written about positioning utilizing cellular networks like 3G/ (Universal Mobile Telecommunications System) and 4G/LTE (Long Term Evolution). From last studies these systems have shown to be insufficient for various applications, including those requiring cm-level accuracy, such as autonomous driving, safety-critical applications, and aircraft location. 5G represents the only technology to reach a precision under $1m$ and dedicated data and pilots (PRS or Positioning Reference Signal) will be included in the standard for this purpose.

Transmissions over 5G-NR are more adaptable than those over earlier standards. Differently from LTE, multiple LTE numerologies are supported in 5G, and an index parameter called μ is used to parameterize the numerology.

In 5G NR, downlink, uplink and sidelink transmissions are arranged into frames with $T_f = 10ms$ duration, each consisting of ten subframes of $T_{sf} = 1ms$ duration. A single frame's and a single subframe's duration are determined by:

$$T_f = (\Delta f_{max} N_f / 100) \cdot T_c$$
$$T_{sf} = (\Delta f_{max} N_f / 1000) \cdot T_c$$

where $\Delta f_{max} = 480 \cdot 10^3 Hz$ and $N_f = 4096$. LTE symbols in a slot in a downlink or uplink frame can be classified as 'downlink', 'flexible', or 'uplink'. In a slot in a downlink frame, the UE shall assume that downlink transmissions only occur in 'downlink' or 'flexible' symbols. In a slot in an uplink frame, the UE shall only transmit in 'uplink' or 'flexible' symbols.

In the table below, Δf stands for Subcarrier Spacing (SCS), T_S for symbol duration, T_{CP} for the Cyclic Prefix duration, N_{slot}^{frame} for the number of slots per frame, and T_{slot} for the slot duration. The Frequency Ranges (FR) that are available for 5G-NR are also flexible:

- FR1 → Transmissions below 7.125 GHz
- FR2 → Transmissions above 24 GHz

The specifications just reported are the ones in accordance with the latest version of 3GPP Release 17 TS [5].

μ	Δf $[kHz]$	FR1	FR2	Cyclic Prefix	T_S $[\mu s]$	T_{CP} $[\mu s]$	N_{slot}^{frame}	T_{slot} $[ms]$
0	15	✓	x	Normal	66.67	4.69	10	1
1	30	✓	x	Normal	33.33	2.34	20	0.5
2	60	✓	✓	Normal,Extended	16.67	1.17	40	0.25
3	120	x	✓	Normal	8.33	0.58	80	0.125
4	240	x	✓	Normal	4.17	0.29	160	0.0625
5	480	x	✓	Normal	2.08	0.14	320	0.03125
6	960	x	✓	Normal	1.04	0.07	640	0.015625

Table 1.1: Supported 5G transmission numerologies and relative parameters.

A resource grid with a number of subcarriers equal to $N_{RB}^{\mu} N_{sc}^{RB}$ and a number of LTE symbols equal to $N_{symb}^{subframe,\mu} = 14 \cdot 2^{\mu} - 1$ can be defined for each numerology. A Resource Block (RB) is a collection of $N_{sc}^{RB} = 12$ subcarriers that is contained inside each resource grid and is only defined in the frequency domain. The smallest component of the resource grid, referred to as a Resource Element (RE), consists of one subcarrier in the frequency domain and one LTE symbol in the time domain. We designate the RE by (k, l), where k is the index in frequency domain (relative to the subcarrier) and l denotes the symbol position in time domain, in order to streamline the layout of the resource grid.

The resource grid architecture is depicted in Figure 1.5 below, which also emphasizes some of the most significant stated characteristics.

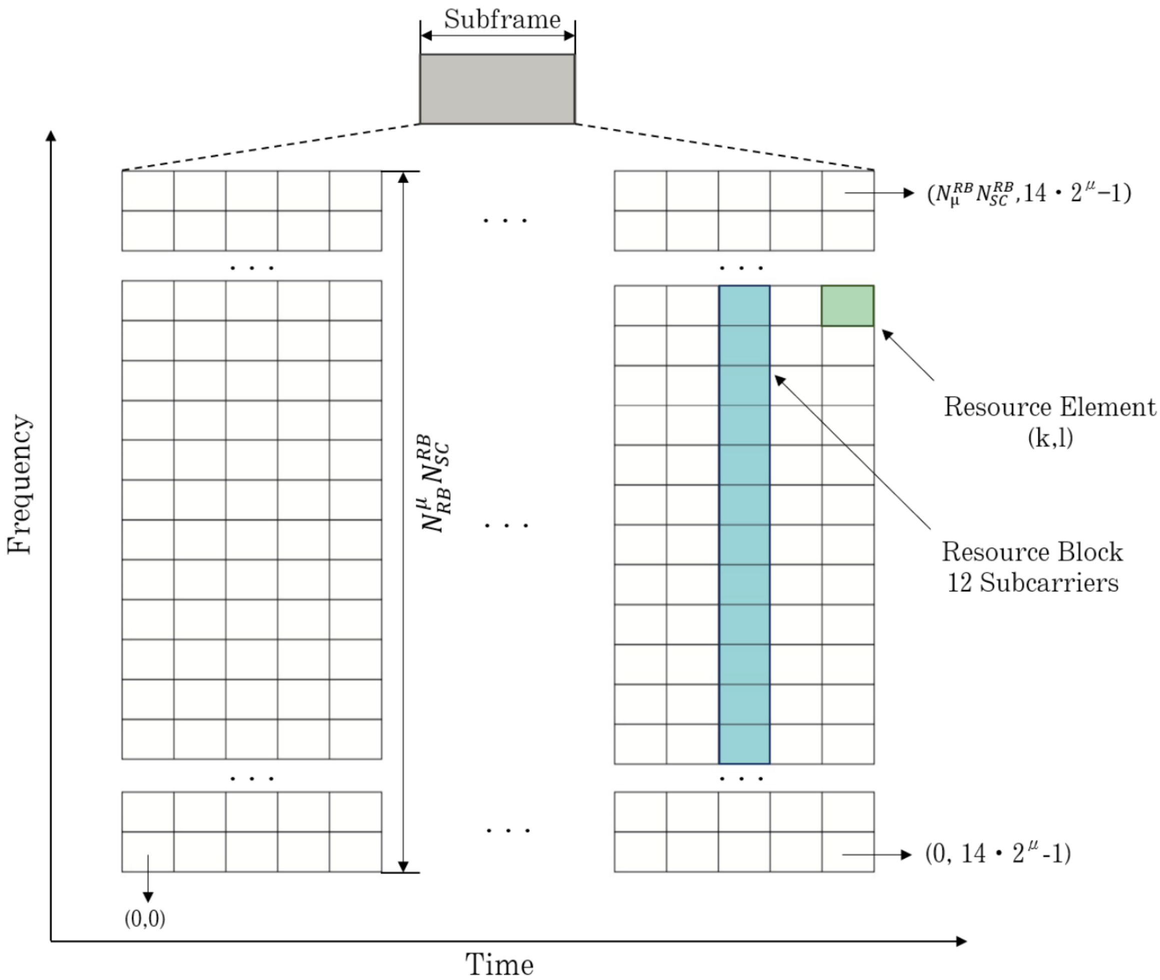


Figure 1.5: 5G NR resource grid definition. The numerology μ determines all physical dimensions.

Determining the maximum transmission bandwidth arrangement is made easier by being aware of the frame structure and resource grid characteristics. Then, the maximum channel bandwidth configuration is calculated as:

$$BW_{max} = N_{RB,max}^{\mu} \cdot \Delta f \cdot N_{sc}^{RB} \tag{1.11}$$

Next, Table 1.2 compiles the major frame construction parameters for 5G.

Description	Symbol
Bandwidth	BW
Numerology	μ
Subcarrier Spacing	Δf
Carrier Frequency	f_c
Number of Slots Per Frame	$N_{slot}^{frame,\mu}$
Number of Slots Per Subframe	$N_{slot}^{subframe,\mu}$
Number of Symbols per Slot	N_{symbol}^{slot}
Number of subcarriers per RB	N_{sc}^{RB}
Maximum number of RBs per μ	$N_{RB,max}^{\mu}$
Frame Time Duration	T_f
Subframe Time Duration	T_sf

Table 1.2: Summary of 5G NR cellular parameters.

1.8. Enabling technologies

The objective of this section is to give an overview on the technological aspect of this thesis, with a brief description of the devices taken into consideration for the future testing of the algorithm.

1.8.1. Ultra-wideband technology

The thesis work is focused on the implementation of a localization algorithm, based on the next 5G technology that is to be widely spread in the following 10 years. However, since this technology is not available yet on the market, the real tests taking place in the circuit and also road testing will be executed using the Ultra WideBand (UWB) technology [16]. The choice to use UWB with respect to other technolgies springs up from some evaluations in terms of bandwidth and performance [13].

Ultra WideBand (UWB) is a short-range wireless communication protocol, like Wi-Fi or Bluetooth, uses radio waves of short pulses over a spectrum of frequencies ranging from 3.1 to 10.5 GHz in unlicensed applications. Commercially available systems typically consist of a network of synchronized UWB receivers which track a large number of small, battery powered UWB transmitters.

[Aggiungere immagine di antenna UWB usata per test]

The most important bandwidth's features of the UWB, that can be compared with the 5G ones, are highlighted below:

- The wide bandwidth provides immunity against the channel effect in a dense environment and enables very fine time-space resolutions for highly accurate positioning;
- High data rates can be transmitted over a short distance.

Data trasmission can be realized with two alternative strategies:

- Ultra-short pulses (*picosecond* range), which covers all frequencies simultaneously (also called impulse radios);
- Subdividing the total UWB bandwidth into a set of broadband Orthogonal Frequency Division Multiplexing (OFDM) channels.

Cost-effectiveness of the first approach comes at the expense of a lower SNR (Signal-to-Noise Ratio). As the signal is directly emitted via the UWB antenna, impulse radio transmission typically does not require the use of a carrier, which results in less complexity than classic narrow-band transceivers (i.e., simpler transceiver architecture). The second strategy uses the spectrum more effectively, improves performance and data throughput at the cost of complexity (i.e., requires signal processing) and power consumption that are raised.

1.8.2. Inertial Measurement Unit

A way to improve the tracking performance (especially the positioning accuracy), can be to use also the information coming from an Inertial Measurement Unit (IMU) mounted on the vehicle. An IMU is a device that uses accelerometers and gyroscopes to detect linear acceleration and rotational rate, it can be part of an Inertial Navigation System (INS), and it actually forms the backbone for the navigation and control of many real commercial and military vehicles such as crewed aircraft, missiles, ships, submarines, and satellites.

Figure 1.6: Inertial Measurement Unit

The combined usage of IMU with all the technologies and methods described in the previous chapters can lead to better performance, more reliability. The combination just mentioned is what it has been done in this thesis, in fact it's possible to see in the MatLab code implemented that there is a section that accounts for the implementation of a virtual IMU sensor with the same characteristics of the real one used. Specifically, the IMU sensor considered is the *DC Perception - Lean*. In this way it was possible to manage the information provided by that device, and to include them for the final estimation.

IMUs are characterized by some technical specifications in order to provide an idea of their applicability for a determined task. They depend also on the components that they are equipped with, and these specifications usually are:

- Supply voltage and current;

- Operating temperature range;
- Acceleration range;
- Angular rate range;
- Magnetic field range (in case it’s equipped with a magnetometer).

2 | Models overview

The aim of this chapter is to define the system model considered for the implementation of an algorithm suited for performing a vehicle localization, and then tracking of its position, using a hybrid solution based on the exploitation of the data coming from both GNSS and 5G standards.

A fundamental part in order to implement a tracking positioning algorithm is the choice of the motion model to take into consideration for simulating trajectories and to obtain them in the best possible way. In the following they are illustrated all the motion model considered for the generation of such trajectories and the implementation of the algorithm.

2.1. Nearly Constant Velocity Motion Model

The first model described is the Nearly Constant Velocity (NCV) motion model. Essentially, it's characteristic of vehicle running on highways, in fact a vehicle in this kind of environment tends to maintain a constant velocity, or almost a constant velocity, during all the trip. Not by chance, the first scenario where autonomous driving vehicles are expected to be applied is this one, since it's easier to manage all the tasks of a human driver, thanks to a reduced number of obstacles and actors.

In this model, the state vector is composed by both UE position and velocity, with the acceleration considered as a zero-mean white Gaussian component for each direction. For the NCV motion model, vectors and matrices are defined as follows:

$$\mathrm{u(t)} = \begin{bmatrix} u_{x,t} \\ u_{y,t} \end{bmatrix}; \qquad \mathrm{v(t)} = \begin{bmatrix} v_{x,t} \\ v_{y,t} \end{bmatrix}$$

$$\mathrm{x(t)} = \begin{bmatrix} u(t) \\ v(t) \end{bmatrix} = \begin{bmatrix} u_{x,t} \\ u_{y,t} \\ v_{x,t} \\ v_{y,t} \end{bmatrix}$$

$$\mathrm{F} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix};$$

$$\mathrm{L} = \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \end{bmatrix};$$

$$\mathrm{Q}_t = \begin{bmatrix} \sigma^2_{x,t} & 0 \\ 0 & \sigma^2_{y,t} \end{bmatrix}.$$

where T indicates the sampling time in seconds, so the interval between a measurement and the next one.

2.2. Nearly Constant Acceleration Motion Model

The Nearly Constant Acceleration (NCA) motion model is introduced to describe the acceleration and braking phases of the vehicle. This is a model suited more for the urban scenario: everyone with an experience as driver can account for a more variability when in a metropolitan environment.

In this case the state vector has also the information regarding the acceleration, while it can be assumed that acceleration's increments for each direction are described by a zero-mean white noise process. Writing down the vectors and matrices:

$$\mathrm{u(t)} = \begin{bmatrix} u_{x,t} \\ u_{y,t} \end{bmatrix}; \qquad \mathrm{v(t)} = \begin{bmatrix} v_{x,t} \\ v_{y,t} \end{bmatrix}; \qquad \mathrm{a(t)} = \begin{bmatrix} a_{x,t} \\ a_{y,t} \end{bmatrix};$$

$$\mathrm{x(t)} = \begin{bmatrix} u(t) \\ v(t) \\ a(t) \end{bmatrix} = \begin{bmatrix} u_{x,t} \\ u_{y,t} \\ v_{x,t} \\ v_{y,t} \\ a_{x,t} \\ a_{y,t} \end{bmatrix};$$

$$\mathrm{F} = \begin{bmatrix} 1 & 0 & T & 0 & \frac{T^2}{2} & 0 \\ 0 & 1 & 0 & T & 0 & \frac{T^2}{2} \\ 0 & 0 & 1 & 0 & T & 0 \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix};$$

$$\mathrm{L} = \begin{bmatrix} \frac{T^2}{2} & 0 \\ 0 & \frac{T^2}{2} \\ T & 0 \\ 0 & T \\ 1 & 0 \\ 0 & 1 \end{bmatrix};$$

$$\mathrm{Q}_t = \begin{bmatrix} \sigma_{x,t}^2 & 0 \\ 0 & \sigma_{y,t}^2 \end{bmatrix}.$$

2.3. Constant Turn Rate Motion Model

The last model described is the Constant Turn Rate (CTR) motion model that, as the previous one, represents a critical situation to manage in particular environments. It is assumed that the vehicle is moving with constant velocity and is performing a turn with a constant turn rate ω. This is one of the possible CTR models, because it depends on the type of principal motion model (in this case the NCV one). In this model the state vector considers UE position and velocity and has also the information about the turn rate ω. It's important to notice that the state transition matrix is non-linear because of its dependence on the state variable ω. Furthermore, the process noise is used to model the uncertain accelerations along x and y directions, caused by the turn rate ω. For clarity, also in this case the state vector and the matrices characterizing the current motion model are written:

$$\mathrm{u(t)} = \begin{bmatrix} u_{x,t} \\ u_{y,t} \end{bmatrix}; \qquad \mathrm{v(t)} = \begin{bmatrix} v_{x,t} \\ v_{y,t} \end{bmatrix}$$

$$\mathrm{x(t)} = \begin{bmatrix} u(t) \\ v(t) \\ \omega \end{bmatrix} = \begin{bmatrix} u_{x,t} \\ u_{y,t} \\ v_{x,t} \\ v_{y,t} \\ \omega \end{bmatrix}$$

$$\mathrm{F} = \begin{bmatrix} 1 & 0 & \frac{\sin(\omega T)}{\omega} & -\frac{1-\cos(\omega T)}{\omega} & 0 \\ 0 & 1 & \frac{1-\cos(\omega T)}{\omega} & \frac{\sin(\omega T)}{\omega} & 0 \\ 0 & 0 & \cos(\omega T) & -\sin(\omega T) & 0 \\ 0 & 0 & \sin(\omega T) & \cos(\omega T) & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix};$$

$$\mathrm{L} = \begin{bmatrix} \frac{T^2}{2} & 0 & 0 \\ 0 & \frac{T^2}{2} & 0 \\ T & 0 & 0 \\ 0 & T & 0 \\ 0 & 0 & 0 \end{bmatrix};$$

$$\mathrm{Q}_t = \begin{bmatrix} \sigma^2_{x,t} & 0 & 0 \\ 0 & \sigma^2_{y,t} & 0 \\ 0 & 0 & 0 \end{bmatrix}.$$

3 | Bayesian tracking filters

In this chapter a general overview of the basics about filtering methods is provided, with a focus on the kind of filters applied for the proposed solution, making the point on the differences between the used filters with respect to others available from the literature.

3.1. Kalman Filter

The design of the Kalman Filter (KF) is usually made passing through the state-space representation of the linearized model.
The Kalman Filter is a state observer with optimality properties for systems subjected to stochastic disturbances. The structure of a typical system to which the KF can be applied is the following:

$$\dot{x}(t) = Ax(t) + Bu(t) + v_x(t)$$
$$y(t) = Cx(t) + v_y(t)$$

where $v = \left[\begin{smallmatrix} v_x \\ v_y \end{smallmatrix}\right]$ is a white gaussian noise with expected value equal to zero and covariance matrix V.

$$V = \begin{bmatrix} \tilde{Q} & Z \\ Z' & \tilde{R} \end{bmatrix} \tag{3.1}$$

It can usually be assumed that the noises acting on the states and on the output are uncorrelated, to obtain an easier design problem. Essentially, it's possible to set $Z = 0$, and assume that $\tilde{Q} \geq 0$,$\tilde{R} \geq 0$.

The choice of the matrices $\tilde{Q}$ and $\tilde{R}$ is often difficult. $\tilde{R}$ can be obtained by recalling that its diagonal elements are the variances of the available output measurements, so that it ca be defined considering the accuracy and sensibility of the sensors. Using a small value means that the measurement is very affordable, but the problem is that if this one is highly noisy the model will follow exactly the error. On the contrary, the estimate of $\tilde{Q}$ is usually more difficult because it represents the uncertainty in the process model. Simplified models can be used, considering some uncertainty through the matrix $\tilde{Q}$. In some cases, $\tilde{Q}$ and $\tilde{R}$ can be considered as free design parameters.

In the problem under study, the target state is written as $x_t = [x_{1,t}, ..., x_{K,t}]^T$, and it includes all the kinematics information parameters, whereas the total number N of available measurements at time instants t are grouped in a vector of noisy measurements $\rho(t) = [\rho_{1,t}, ..., \rho_{K,t}]^T$. The models considered for the formulation problem are:

$$x_t = f_t(x_{t-1}, w_{t-1})$$
$$\rho_t = h_t(x_t, n_t)$$

where f_t and h_t are the time-varying system and the measurement model, respectively. The terms w_t and n_t are instead the noises applied to the just described functions, and they are assumed to be independent and uncorrelated Gaussian random processes. The estimation of x_t is based on the posterior pdf (probability density function) $p(x_t|\rho_{1:t})$ which embodies all the information on x_t available at time t, obtained from the current data ρ_t and the prior knowledge drawn past observations. It's to be underlined that the posterior pdf is computed starting from that at previous step, $p(x_{t-1}|\rho_{1:t-1})$, by two steps:

- Prediction: it uses the system model written above to predict the state pdf forward from $t-1$ to t. Due to process noise, prediction generally spreads the state pdf. The prior pdf is obtained from the posterior pdf of the previous step via the Chapman–Kolmogorov equation [11], and the transition pdf $p(x_t|x_{t-1})$ can be calculated from the system model, using the knowledge of $f_t(\cdot)$ and of the driving process w_t;
- Update: it uses the measurement model written above too to adjust the predicted pdf with the latest measurement ρ_t. The posterior pdf (pdf of x_t after the data ρ_t has been observed) is the product of the likelihood and the prior (pdf of x_t before the data is observed). The likelihood is obtained from the measurement model, using the knowledge of $h_t(\cdot)$ and the measurement noise n_t statistics.

The assumptions to do in order to apply the Kalman Filter are: system and measurement models known and linear ($f_t(\cdot)$ and $h_t(\cdot)$), and also that the driving process w_t and the measurement noise n_t are Gaussian distributed with known parameters. The model to consider for the development of a Kalman Filter for localization purposes is the following:

$$x_t = F_t x_{t-1} + L_t w_{t-1}$$
$$\rho_t = H_t x_t + n_t$$

with:

$$w_t \sim \mathcal{N}(0, Q_t); \quad n_t =\sim \mathcal{N}(0, R_t) \tag{3.2}$$

and the matrices are allowed to be time-variant. It can now be specified the prediction and update steps in relation with the just mentioned model, so:

$$\begin{aligned}\hat{x}_{t|t-1} &= F_t\hat{x}_{t-1|t-1}\\ P_{t|t-1} &= F_tP_{t-1|t-1}F_t^T + Q_{t-1}\end{aligned}$$

$$\begin{aligned}\hat{x}_{t|t} &= \hat{x}_{t|t-1} + G_t(\rho_t - H_t\hat{x}_{t|t-1}) = \hat{x}_{t|t-1} + G_t\epsilon t|t-1\\ P_{t|t} &= P_{t|t-1} - G_tH_tP_{t|t-1}\\ G_t &= P_{t|t-1}H_t^T(H_tP_{t|t-1}H_t^T + R_t)^{-1}\end{aligned}$$

In the definitions above, it is noticeable the fundamental role of G_t: it's the Kalman gain and it can be computed at each iteration in order to match the dynamic changing of the variables.

The problem of the Kalman filtering is that it accounts only for linear problems: this means that, in order to apply it, it's necessary to perform a linearization of the system model. This would lead to a solution that will not reach the requirements, and this is quite obvious since it would mean to exclude all the non-linear behaviours that are affecting the motion of a vehicle while running. For this reason, a better idea can be to use the extended version of the Kalman Filter, described in the next section.

3.2. Extended Kalman Filter

It may be a good idea, if the system or measurement models are non-linear, to linearize the model functions $f(\cdot)$ and /or $h(\cdot)$ around the current location fix and approximate the PDFs as Gaussian. The suggested linearization is the Taylor expansion truncated to the first term:

$$f_t(x_{t-1}) \approx f_t(\hat{x}_{t-1|t-1}) + \underbrace{\left.\frac{\partial f_t(x_{t-1})}{\partial x_{t-1}}\right|_{x_{t-1|t-1}=\hat{x}_{t-1|t-1}}}_{\hat{F}_t}(x_{t-1|t-1} - \hat{x}_{t-1|t-1})$$

$$h_t(x_t) \approx h_t(\hat{x}_{t|t-1}) + \underbrace{\left.\frac{\partial h_t(x_t)}{\partial x_t}\right|_{x_t=\hat{x}_{t|t-1}}}_{\hat{H}_t}(x_t - \hat{x}_{t|t-1})$$

where $\hat{F}_t$ and $\hat{H}_t$ are the system model matrix and the measurement model matrix respectively. The prediction and update steps are the same of the ones described before for the Kalman Filter, the only difference is that for the mean evaluation we use the non-linear functions:

$$\begin{aligned}\hat{x}_{t|t-1} &= f_t\hat{x}_{t-1|t-1}\\ P_{t|t-1} &= \hat{F}_t P_{t-1|t-1}\hat{F}_t^T + Q_{t-1}\end{aligned}$$

$$\begin{aligned}\hat{x}_{t|t} &= \hat{x}_{t|t-1} + G_t(\rho_t - h_t\hat{x}_{t|t-1}) = \hat{x}_{t|t-1} + G_t\epsilon t|t-1\\ P_{t|t} &= P_{t|t-1} - G_t\hat{H}_t P_{t|t-1}\\ G_t &= P_{t|t-1}\hat{H}_t^T(\hat{H}_t P_{t|t-1}\hat{H}_t^T + R_t)^{-1}\end{aligned}$$

Linearization is an approximation that does not guarantee optimality, and if the model functions are strongly non-linear or random noises are not Gaussian, then the Gaussian assumption is not realistic and EKF is not a good solution.

In the following another possible solution will be described, that allows to consider non-linear models without previously passing through the linearization procedure.

3.3. Unscented Kalman Filter

The Unscented Kalman Filter (UKF) is a particular kind of Bayesian filter that is used to overcome two main problems of the previously described EKF [10]:

- Poor approximating properties of the first order approximation;
- Requirement for the noises to be Gaussian.

The technique behind this filter is the so-called unscented transform (UT) that is a deterministic sampling technique to pick a minimal set of sample points (σ-points) around the mean. Essentially, the objective is to find a transformation that can approximate the mean and covariance of a random vector when it is transformed by a non-linear function. So, the main difference between EKF and UKF is that the first one performs a first order accuracy estimation of the state, whereas the UKF is able to obtain the same estimation accurate at the third order (Taylor series expansion) if considering Gaussian noises.

As final choice, the UKF has been used in the developed algorithm for the estimation of the UE position. After some evaluations on the implementation time and the trade-off between this time and the difficulty for writing the code itself, the choice has been to use some already implemented functions in the MatLab software used for coding and simulating the algorithm.

These functions are quite easily used but there are some low lights to underline, because when using such functions it's important to be careful that the inputs are well-defined and not in conflict on what they are expecting. In order to be clear, one of these points is to pay attention to the structure of the state vector: for example the MatLab function for Nearly Constant Velocity (NCV) motion model has the following structure:

$$\mathrm{x(t)} = \begin{bmatrix} x \\ v_x \\ y \\ v_y \end{bmatrix}$$

and it's important to arrange our information to send to the algorithm in a way that doesn't go into conflict with this structure.

The Unscented Kalman Filter estimates the state of a process governed by a nonlinear stochastic equation [4].

$$x_{k+1} = f(x_k, u_k, w_k, t)$$

where x_k is the state at step k. $f(x_k, u_k, w_k, t)$ is the state transition function, u_k are the controls on the process. The motion may be affected by random noise perturbations, w_k. The filter also supports a simplified form:

$$x_{k+1} = f(x_k, u_k, t) + w_k$$

In the Unscented Kalman Filter, the measurements are also general functions of the state:

$$z_k = h(x_k, v_k, t)$$

where $h(x_k, v_k, t)$ is the measurement function that determines the measurements as functions of the state. Typical measurements are position and velocity or some function of these. The measurements can include noise as well, represented by v_k. Again there is a simpler formulation:

$$z_k = h(x_k, t) + v_k$$

These equations represent the actual measurements and the actual motion of the object. The exact contribution of noise at each phase, however, is uncertain and cannot be modeled. Only the noise's statistical features are known.

3.4. Interactive Multiple Model

A wide reflection on the localization problem can lead to a deep evaluation of what is really challenging in the problem under study. Vehicles may abruptly alter their dynamics due to traffic lights, crosswalks, and erratic traffic circumstances, so in other terms, it can be difficult to perform an accurate state estimation of a UE with fluctuating dynamics (as a vehicle).

Due to these conditions, the estimation mentioned above can be very hard considering the vehicle moving with a single motion model. After this evaluation, here it's suggested to use the so-called Interactive Multiple Model (IMM). This tool is a really powerful means, with a structure that allows to efficiently control many filters reflecting several potential maneuver states, each with a particular motion model. Essentially, in order to provide a more accurate state estimate of targets with changing dynamics, the IMM algorithm combines state hypotheses from various filter models. The IMM algorithm has three desirable properties: it is recursive, modular, and has fixed computational requirements per cycle. In each cycle three major steps can be individuated: interaction (mixing), filtering, and combination [18]. The initial conditions are established for a specific model-matched filter in each step by combining the state estimates produced by all filters from the previous time step, presuming that this particular model is the correct model at the current time step. The state and covariance of the Gaussian density at that particular time step are then estimated using chosen method of filtering for each model, which is followed by a weighted combination of all the updated state estimates provided by the filters. A collection of Kalman filters, a probability vector μ_t, and a Transition Probability Matrix (TPM) are needed for the IMM.

> TPM: Transition Probability Matrix defined for each model corresponds to the probability that the filter switches from this model to another model in one second.
>
> $\mu_{m,t}$: is the probability that the target is in model m at time instant t.

The probabilities in the TPM can be written as follows for the case of M models and are normally believed to be known a priori:

$$\Lambda = \begin{bmatrix} p_{1,1} & \cdots & p_{1,M} \\ \vdots & \ddots & \vdots \\ p_{M,1} & \cdots & p_{M,M} \end{bmatrix}$$

and it has to satisfy the constraint:

$$\sum_{n=1}^{M} p_{m,n} = 1, \forall m$$

We can assert that the weights are represented by the model probabilities $\mu_{m,t}$, and the overall state estimate provided by the IMM filter method is a weighted combination of each of the individual Kalman Filter estimates.

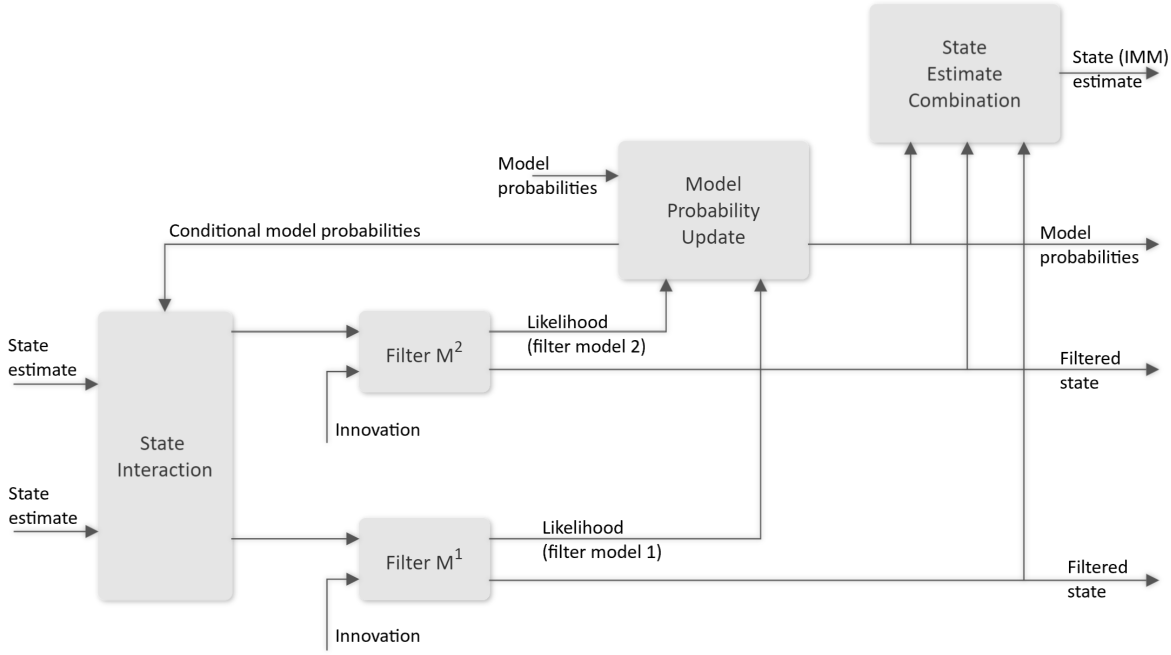


Figure 3.1: Structure of a block diagram of the IMM algorithm with two filter models

In the figure above, there is a block diagram of the IMM algorithm with only two filter models, just to give the reader an idea of the working principle.

The IMM algorithm must be correctly implemented in order to produce the best results. It has to be built taking into account the choice of motion models and the covariance of each model's process noise. Additionally, various transition probability selections have a direct impact on how well the IMM performs. Last but not least, it should be stressed that precise management of the various filter models is essential for limiting algorithm calculations and improving algorithm efficiency [7].

As a *self-adjusting variable-bandwidth filter*, the IMM estimator is an ideal choice for tracking moving targets.

3.5. Satellite-based method's filters

For what concerns the satellite-based method for localization, all the functions called by the already existing algorithm to build the filter were the ones available in the MatLab software for the motion model part because this one didn't need particularly customized functions. The measurement model function was instead written by hand, in order to be used also for the hybrid localization in next steps of implementation if needed. Basically, the following functions were used to consider the motion model:

Model	**Type**	**Function**
Nearly-Constant Velocity	*StateTransitionFcn* *MeasurementFcn*	`constvel` `measModCV_GNSS`
Nearly-Constant Acceleration	*StateTransitionFcn* *MeasurementFcn*	`constacc` `measModCA_GNSS`
Constant Turn Rate	*StateTransitionFcn* *MeasurementFcn*	`constturn` `measModCTR_GNSS`

Table 3.1: GNSS motion models' functions

3.6. Range-based method's filters

For what concerns the range-based method for localization, the functions used as measurement model were different from the ones already implemented in the software because there was the necessity to handle a totally different kind of information. In these filters some ad hoc functions have been created in order to obtain a precise type of data as output. So, a measurement function has been created for each motion model, and used instead of the *MeasurementFcn* already existing.

The state transition functions, differently, have been modeled using the pre-existing function available on the software because it was not of our interest for the final aim.

The choice to use some customized function for the measurement model in this case was due to the fact that for the 5G localization, TDoA measurements have been used in this thesis. These measurements constitutes a vector of dimension 9x1 since we have ten Base Stations available, because $NB - 1$ TDoA are calculated from one of the BSs, called *master AP* in the code. This one can change at every loop iteration of the prediction steps because it is calculated taking into consideration which is the BS with the lowest received power at the specific time instant.

Model	**Type**	**Function**
Nearly-Constant Velocity	*StateTransitionFcn* *MeasurementFcn*	`constvel` `measModCV_5G`
Nearly-Constant Acceleration	*StateTransitionFcn* *MeasurementFcn*	`constacc` `measModCA_5G`
Constant Turn Rate	*StateTransitionFcn* *MeasurementFcn*	`constturn` `measModCTR_5G`

Table 3.2: 5G motion models' functions

4 | Final simulations and results

The previous chapter contains the explanation of the system model and the features of the proposed algorithm for the position estimation problem, on the basis reported in the previous chapters. Here the will is to show the results reached on simulation with a first analysis, in order to provide an idea of the accuracy that can be achieved by the suggested solution.

4.1. Scenario details

The scenario for all the tests and the data collection used as basis for the implementation and simulation of the proposed algorithm is the race circuit in Castelletto.

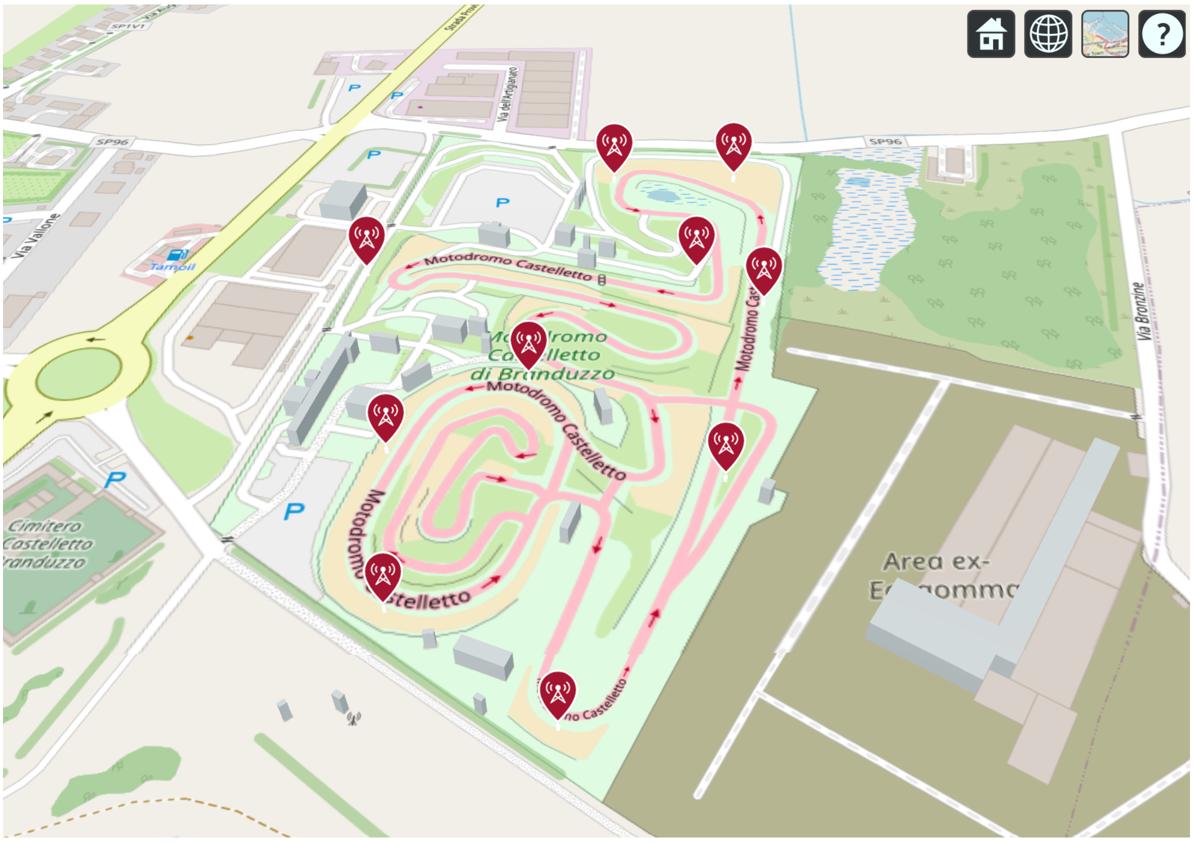
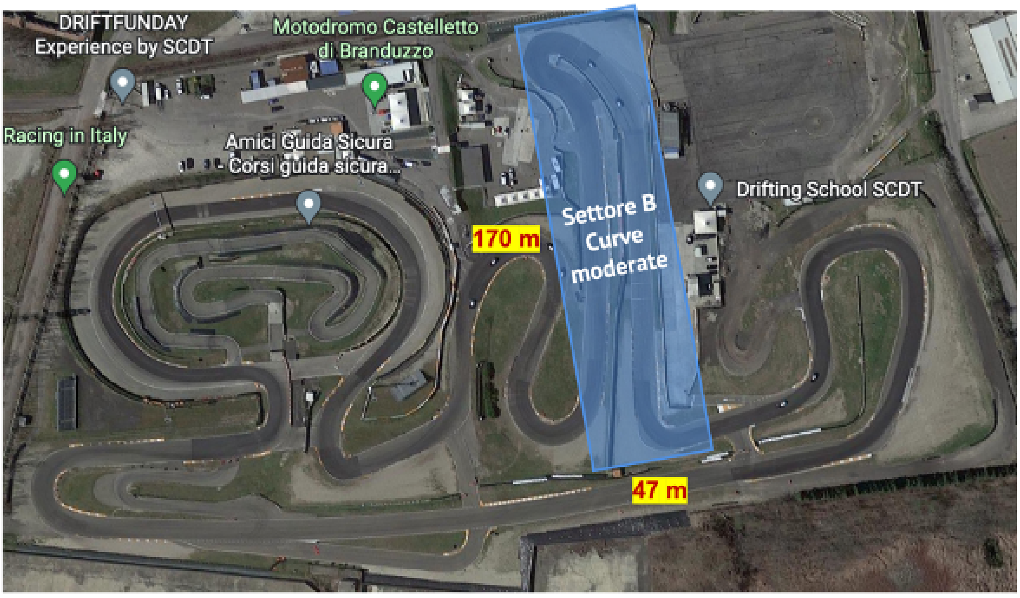


Figure 4.1: Motordrome scenario and layout of the Base Stations

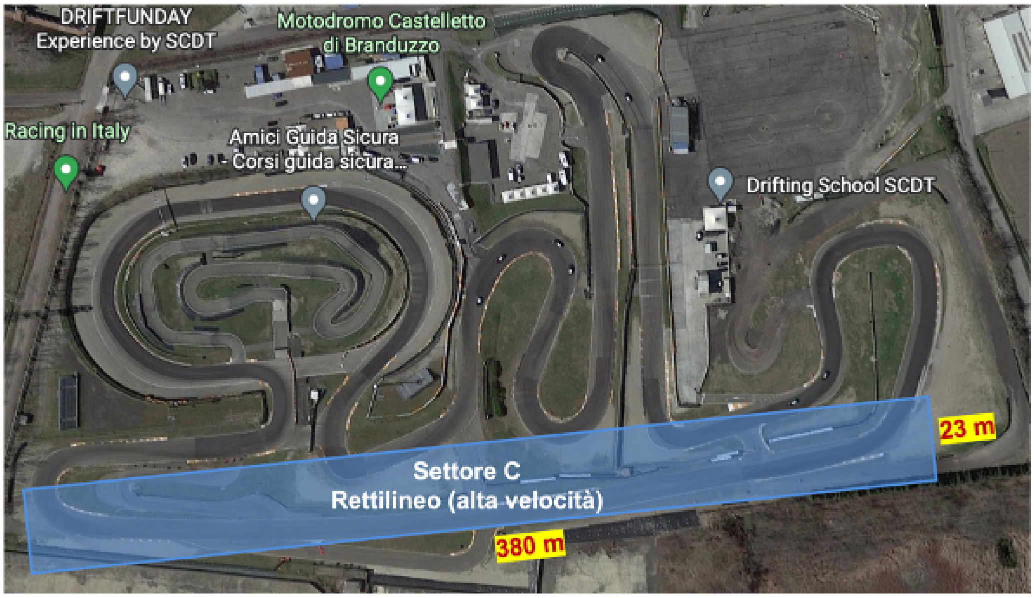
This racetrack has been evaluated as a good benchmark because of its characteristics: it has all the specifications useful to simulate a real speedway scenario. It can be divided into three sectors, each one with a specific conformation, in fact:

- **Sector A**: this is the piece with all the curves.

- **Sector B**: this is the part that is like a mix of the others considered and merges all the characteristics.



- **Sector C**: it is the part of the circuit characterized by the long straight.



As already specified in 2, it was very useful to consider different motion models in order to optimize our localization algorithm, and merging them all in the Interactive Multiple Model (IMM). In this way it was possible to consider each trait of the trajectory in the best possible way. The division of the speedway in sectors has been also a necessary procedure from organizational and technical points of view, because of the limited number of available UWB antennas for our tests.

The other scenario consider to test the proposed algorithm for the localization of vehicle is the one below, and is a reduced sector of the previously considered motordrome:

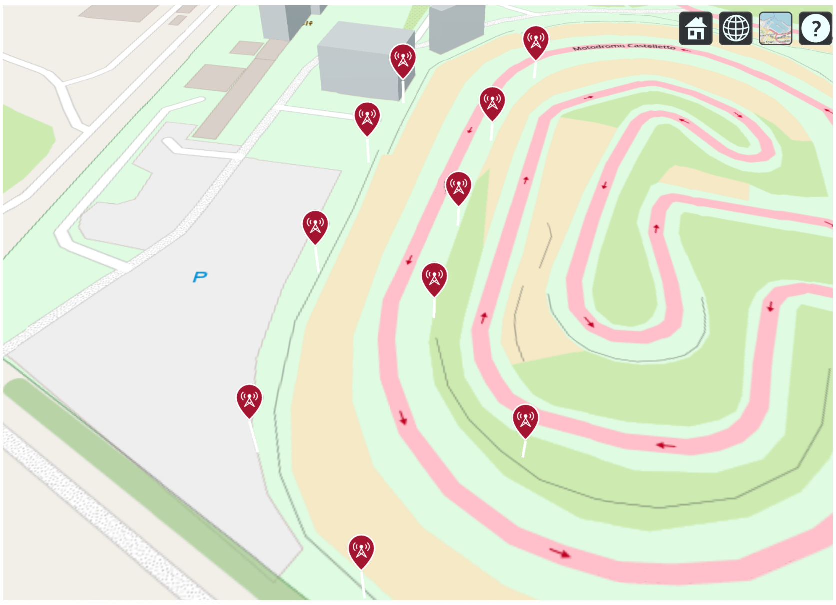


Figure 4.2: Scenario and layout of the Base Stations

4.2. Stand-alone GNSS localization

In the following, the performance of the stand-alone GNSS localization is shown. When describing how well a GNSS receiver acquired a position, the terms accuracy and precision are frequently employed, and it is important to distinguish between them:

- **Precision** → Degree of closeness of observations to their means;
- **Accuracy** → Degree of closeness of an estimate to its true, but unknown value.

Several connections between these two factors are shown in Figure 4.3. The intersection of the cross-hairs indicates the true value, the mean estimate is placed in the shaded area's center, and the estimate's level of uncertainty is shown by the shaded area's radius.

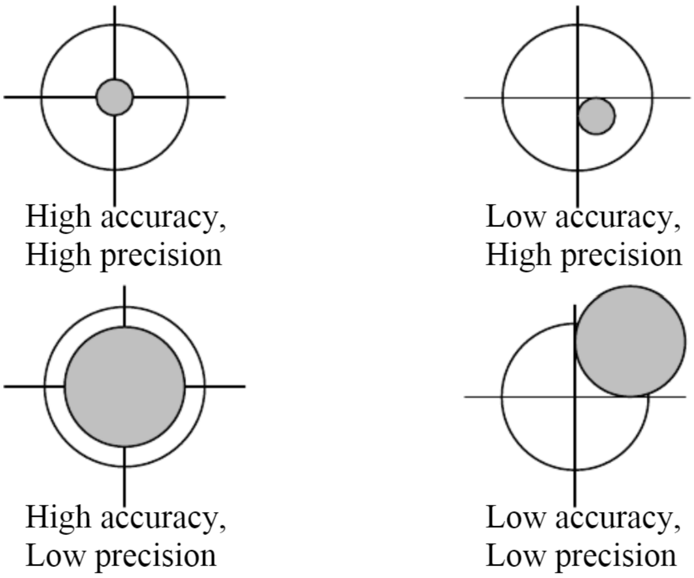


Figure 4.3: Precision vs. Accuracy

Circular Error Probability (CEP) is one of the industry-standard statistical analyses applied to evaluate the precision. The CEP is calculated as a percentage of the total number of points divided by the number of points that are within a defined radius of a given place. In this thesis it is the instrument used to evaluate the goodness of the estimate made by KFs.

The next figure represents the resultant trajectory of the kalman filtering process with IMM model versus the Ground Truth (GT).

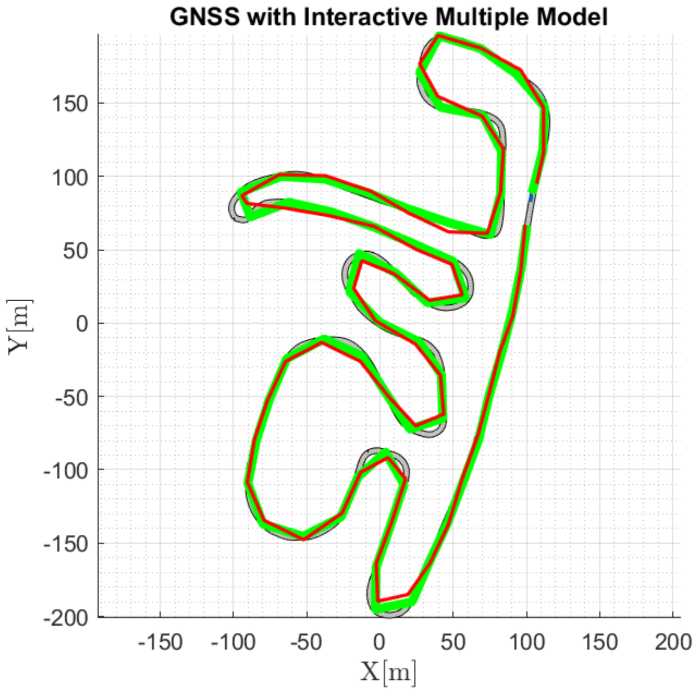


Figure 4.4: Stand-alone GNSS localization: UKF trajectory prediction (red) vs. Ground Truth (green).

It is clearly visible in the following Figure 4.5, and the table below, that the estimation done considering stand-alone GNSS it's not so accurate, and this is mainly due to the number of samples that are available from GNSS.

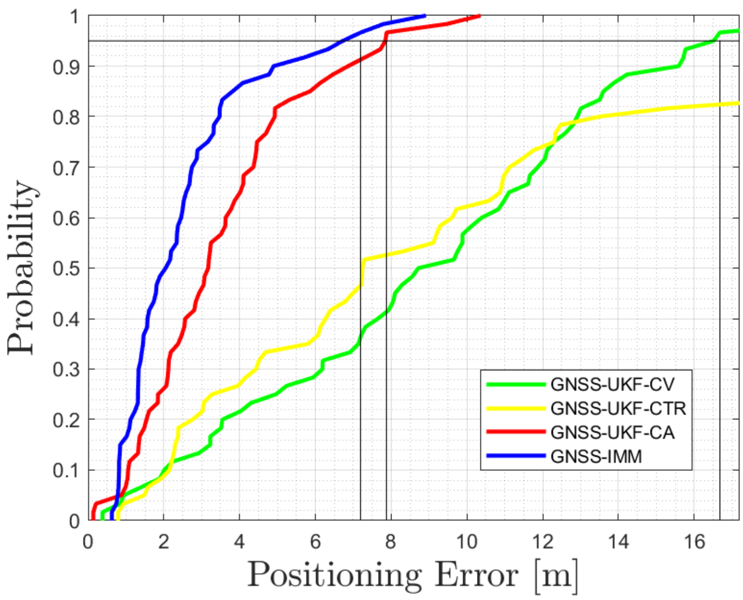


Figure 4.5: CDF of the position error with different motion models. Stand-alone GNSS localization algorithm (Figure 4.4).

Positioning Accuracy [m]				
Motion Model	50%	60%	80%	95%
IMM	1.89	2.37	3.32	6.72
NCA	3.17	3.65	4.92	7.88
NCV	8.72	12.93	14.02	16.5
CTR	7.25	9.61	14.33	27.81

Table 4.1: Summary table of the results in Figure 4.5.

The IMM method, which takes into account all four motion models, consistently beats all other Kalman filters. This is because the IMM reduces positioning error during maneuvers, whereas the previous single models are not appropriate for capturing both maneuvers and non-maneuvers dynamics simultaneously.

It is important to underline that, for what concerns the stand-alone GNSS localization algorithm, the measurement noise covariance matrix R is:

$$\mathrm{R}_{GNSS} = \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 10 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 10 \end{bmatrix}$$

4.3. 5G localization

In the following, the performance of the stand-alone 5G localization is shown. First, considering a simulated scenario of the motordrome in 4.2 it is clearly visible that the 5G performances are much better than the once obtained by the only GNSS:

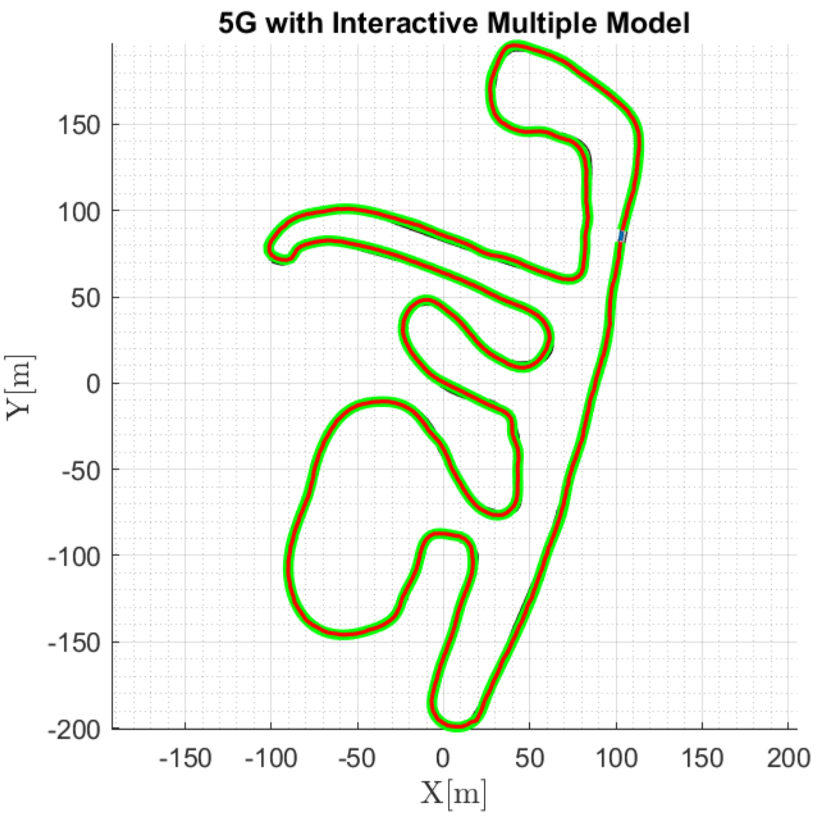


Figure 4.6: 5G localization: UKF trajectory prediction (red) vs. Ground Truth (green).

The figure above clearly highlights the goodness of the localization using 5G technology and now a short analysis of the performance of such a technology will be exposed.

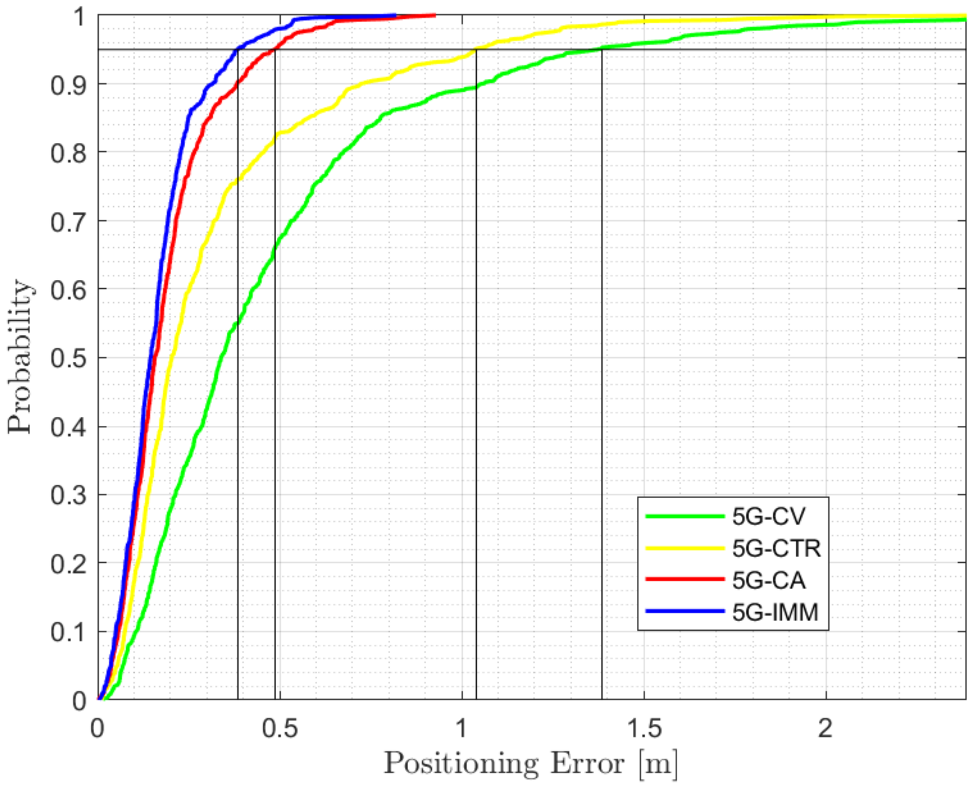


Figure 4.7: CDF of the position error with different motion models. 5G localization algorithm (Figure 4.6).

Positioning Accuracy [m]				
Motion Model	50%	60%	80%	95%
IMM	0.15	0.17	0.22	0.39
NCA	0.16	0.19	0.27	0.49
NCV	0.34	0.43	0.46	1.38
CTR	0.21	0.25	0.68	1.04

Table 4.2: Summary table of the results in Figure 4.7.

From the Table 4.2 it can be seen that the IMM easily have better performance with respect to the single motion models. The localization with 5G technology is characterized by a maximum error, in the 95% of the cases, equal to 39 cm with such a filter as method of prediction, and this is near the requirements from 3GPP standard.

Another scenario taken into consideration to validate the proposed algorithm for 5G localization is a real reduced section of the previously considered motordrome, and in the following there is an analysis regarding also this one.

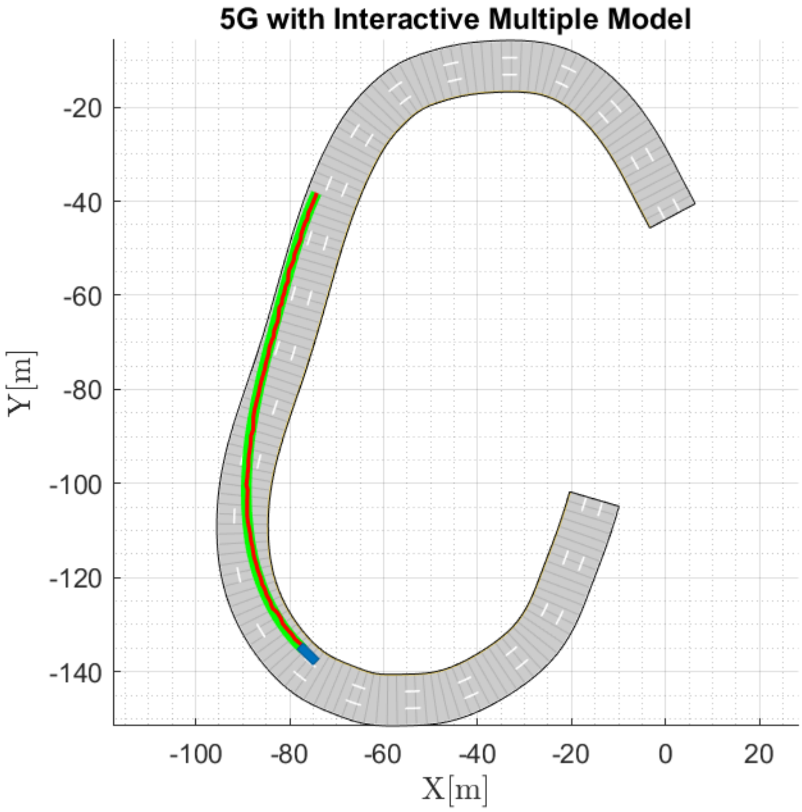


Figure 4.8: 5G localization: UKF trajectory prediction (red) vs. Ground Truth (green).

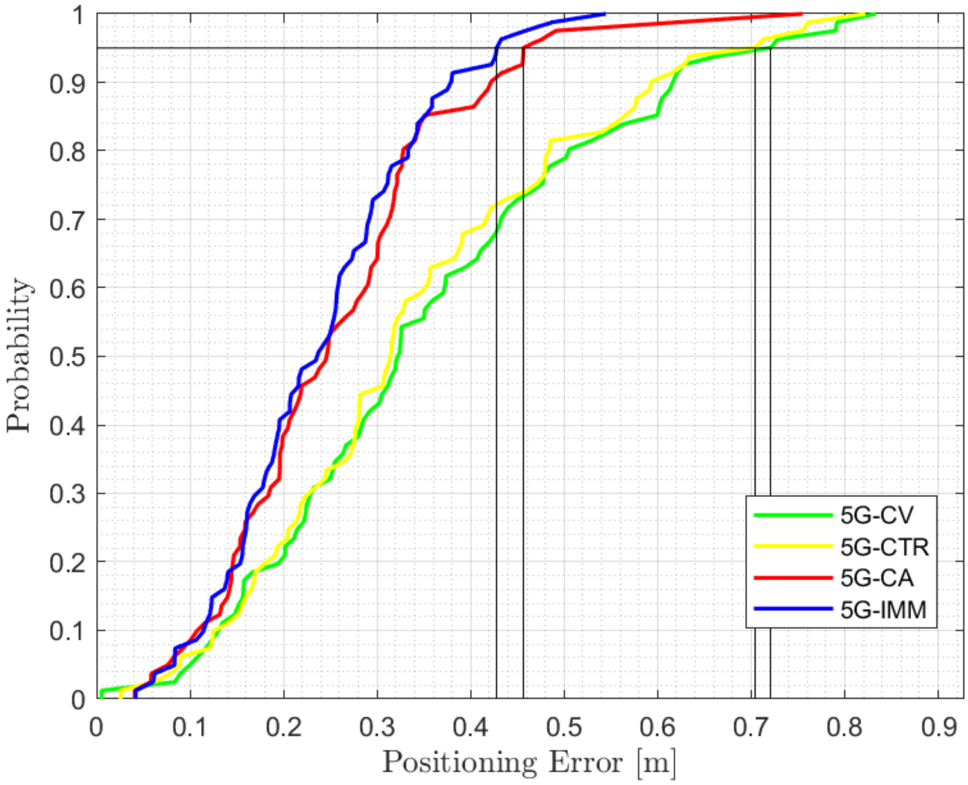


Figure 4.9: CDF of the position error with different motion models. 5G localization algorithm (Figure 4.8).

Positioning Accuracy [m]				
Motion Model	50%	60%	80%	95%
IMM	0.236	0.258	0.33	0.43
NCA	0.246	0.288	0.33	0.46
NCV	0.322	0.351	0.505	0.72
CTR	0.314	0.372	0.485	0.70

Table 4.3: Summary table of the results in Figure 4.9.

4.4. Hybrid localization

Once finished to describe in a quantitative and qualitative way both the satellite-based method and the range-base method, in this section the hybridization of the different technologies is performed in order to explain how much one can influence the other and in which way. Some difficulties have been encountered during this part of the thesis, but it's author's opinion to underline such problems in order to leave some hints for reflection for further development of this work.

4.4.1. 5G localization with additional on-board IMU sensor

This last paragraph put the light on the really aim of the thesis: to show that there is the possibility to obtain some advantages by including the information from an inertial sensor mounted on the vehicle for the localization task. Essentially, a virtual IMU sensor has been modeled and used to help the previously described technologies in their objective.

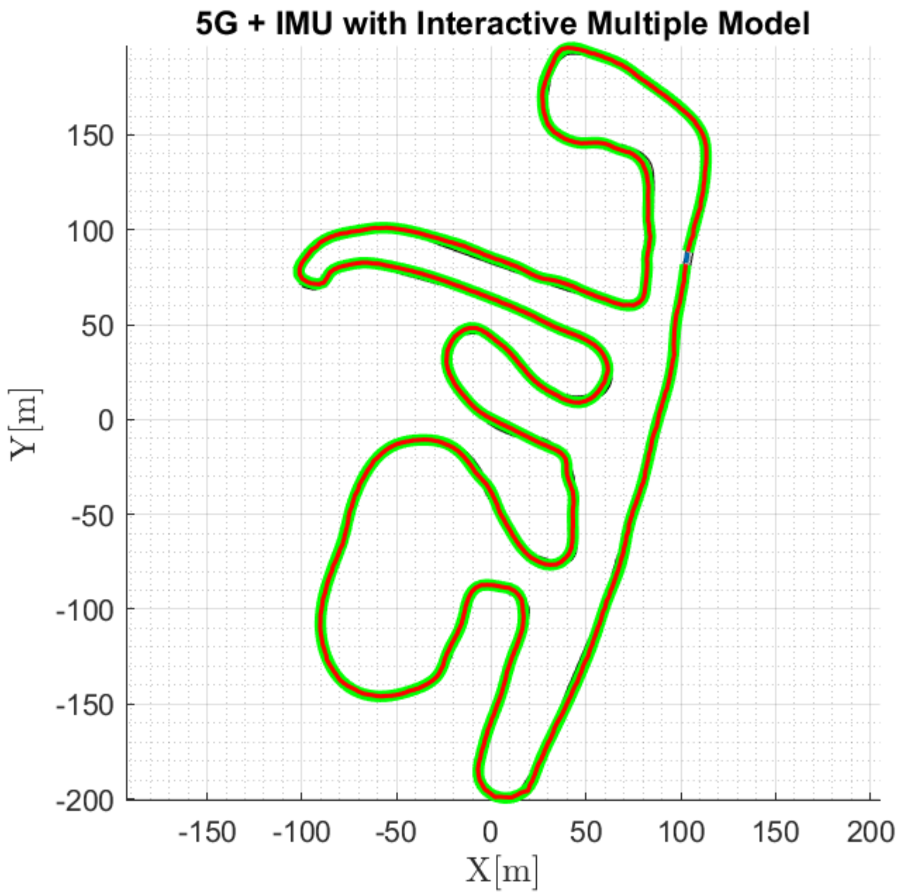


Figure 4.10: Hybrid 5G/IMU localization: UKF trajectory prediction (red) vs. Ground Truth (green).

In the following the obtained result is shown, only using the Interactive Multiple Model (IMM), with a direct comparison with 5G localization:

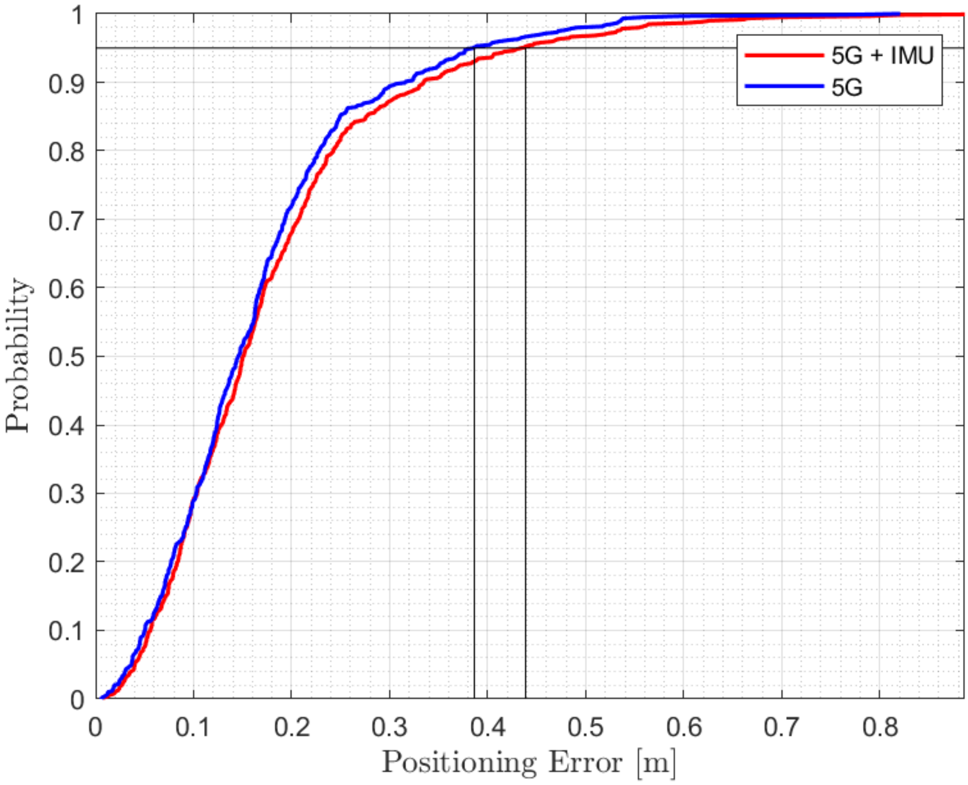


Figure 4.11: CDF of the position error with IMM. Hybrid 5G/IMU vs. 5G localization algorithm (Figure 4.10).

Positioning Accuracy [m]				
Technology	50%	60%	80%	95%
5G	0.15	0.17	0.22	0.39
5G/IMU	0.15	0.17	0.24	0.43

Table 4.4: Summary table of the results in Figure 4.11.

It is visible from the just shown graphics that the hybridization of 5G and IMU is able to obtain results comparable to the stand-alone 5G, and this may be due to parameters' tuning reasons. However, these results seems to be very good considering that they strongly depend also on the quality of the sensor used, in terms of scale factor, measurement noise, and constant error, as explained in Section 0.2; the scale factor is influencing a lot the performance of the sensor by sudden accelerations and/or rotations, and we are considering a circuit as testing scenario so it has to be taken into consideration for sure.

Another scenario taken into consideration to validate the proposed algorithm for 5G/IMU localization is a real reduced sector of the previously considered motordrome, and in the following there is an analysis regarding also this one.

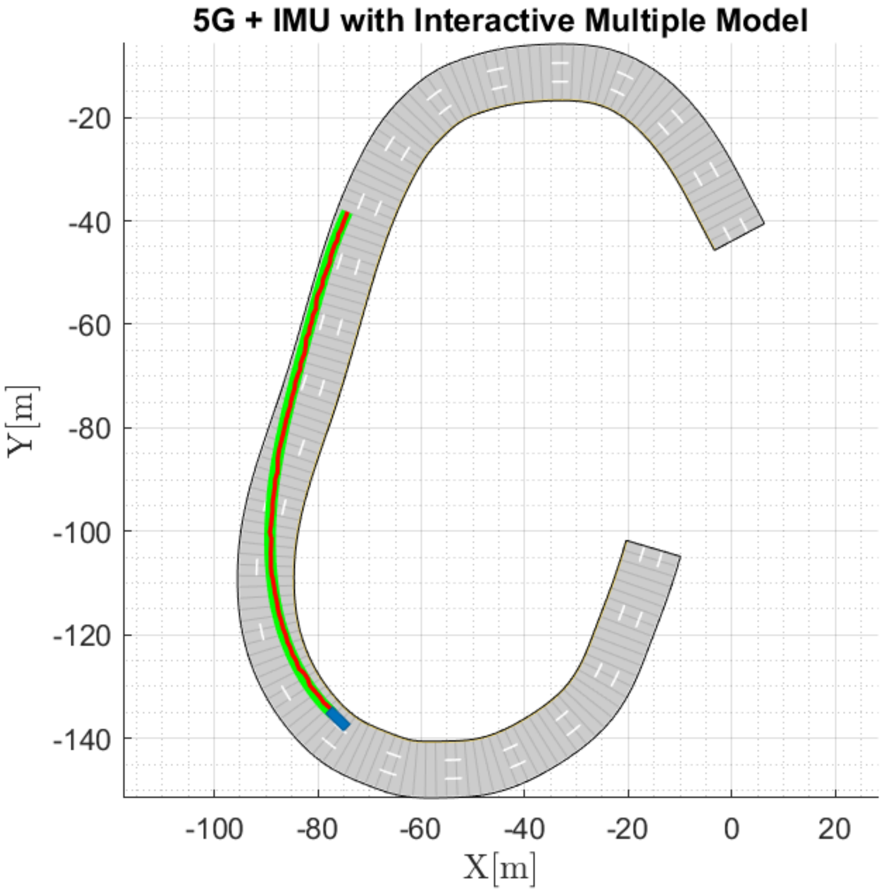


Figure 4.12: Hybrid 5G/IMU localization: UKF trajectory prediction (red) vs. Ground Truth (green).

In the following the obtained result is shown, only using the Interactive Multiple Model (IMM), with a direct comparison with 5G localization:

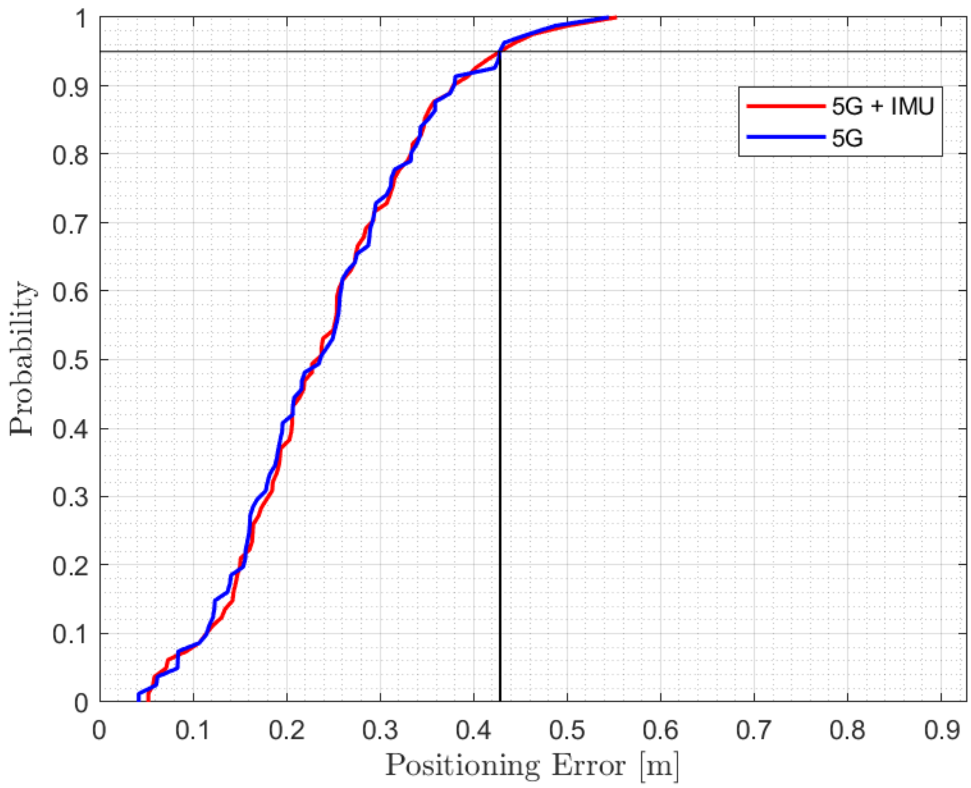


Figure 4.13: CDF of the position error with IMM. Hybrid 5G/IMU vs. 5G localization algorithm (4.12).

Positioning Accuracy [m]				
Technology	50%	60%	80%	95%
5G	0.236	0.258	0.33	0.43
5G/IMU	0.233	0.255	0.33	0.43

Table 4.5: Summary table of the results in Figure 4.13.

For what concerns 5G/IMU localization algorithm, the measurement noise covariance matrix R is:

$$\mathrm{R}_{IMU} = \begin{bmatrix} 100 & 0 \\ 0 & 100 \end{bmatrix}$$

Even if the results produced can suggest to the reader that the additional IMU sensor on the vehicle does not give any improvement to localization algorithms considering only 5G technology, it's important to underline that the proposed solution is considering a virtual Inertial Measurement Unit with a setup made using information of a generic sensor and not the one from which real measurements have been extracted.

5 | Conclusions and future works

This thesis had the aim to develop different types of localization algorithms for real vehicular applications. In order to reach this challenging result, the process have been pursued step-by-step starting from the definition of the assumptions made to define the situation under study, passing through the definition of the characteristics of the technologies and techniques at the basis of all the work, and finally trying to build a final localization algorithm that is able to obtain good performance in terms of accuracy and precision for a future real application. As already reported in the previous chapter, the hybridization of 5G and IMU is able to obtain results comparable to 5G, and this may be due to parameters' tuning reasons. However, it can be assessed that this work can be a good starting point for a future development, with a specific attention to the last part, so the localization using 5G technology and IMU; and if necessary taking into consideration also the GNSS contribution, even if it is superfluous since it is clear from all this treatment that 5G NR can guarantee more performing results. Furthermore, the usage of 5G for application such as vehicular localization is strictly dependent on the capillarity of the distribution of devices that can support it, and when the right density (in terms of number of devices) will be reached, the support of GNSS may be not required. The contribution of cheap sensors, like IMU, placed on the vehicle can be an additional value only if control systems on-board will be able to manage and correct all the errors due to different noisy components IMU sensors suffers of. Another point to highlight is that in this thesis it has been considered a 2D localization, whereas for future real application the requirement will be a 3D precise localization probably. The algorithm already contemplates the passage from 2D to 3D localization thanks to the fact that all the code is developed with a almost total parametrization of the functions. It is not the aim of this thesis to analyze the performance in this scenario, but the flexibility of the code is anyway good point.

For future works, some points can be highlighted and summarized here below:

- An adaptive Kalman Filter can be developed and put into action, in order to consider the different sources of instability present in the real scenario, in different manoeuvres;

- More advanced data fusion filters, such as particle filters, can be implemented instead of the Unscented Kalman Filter to get closer to applicability.

It is important to underline that the obtained results could be really interesting and encouraging because not a straight and uncomplicated highway is evaluated, but the algorithm has been tested on scenarios taking into account for all possible common manoeuvres of a real driving situation.

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Acronyms

2D Two Dimensional. 53

2G Second Generation. 4

3D Three Dimensional. iii, 53

3G Third Generation. 17

3GPP Third Generation Partnership Project. 11, 18, 46

4G Fourth Generation. 4, 17

5G Fifth Generation. i, iii, 1, 4, 6, 7, 9, 11, 17–21, 25, 36, 45–53, 57–59

A-GNSS Augmented Global Navigation Satellite System. 2

A-GPS Assisted Global Positioning System. 2

AoA Angle of Arrival. 10, 15–17, 57

BS Base Station. 36

CDF Cumulative Density Function. 43, 46, 48, 50, 52, 57, 58

CEP Circular Error Probability. 4, 42

CTR Constant Turn Rate. 28, 44, 46, 48

D-GNSS Differential Global Navigation Satellite System. 3

D-GPS Differential Global Positioning System. 2

DoA Direction of Arrival. 10

ECI Earth Centered Inertial. 4, 5

EKF Extended Kalman Filter. 32

eMBB Enhanced Mobile Broadband. 9

FR Frequency Range. 17

GNSS Global Navigation Satellite System. i, iii, 2, 3, 11–13, 25, 42–45, 53, 57

GPS Global Positioning System. 2, 4, 5

GT Ground Truth. 42, 43, 45, 47, 49, 51, 57, 58

IMM Interactive Multiple Model. i, iii, 6, 12, 34, 35, 41, 42, 44, 46, 48, 50–52, 57, 58

IMU Inertial Measurement Unit. i, iii, 22, 49–53, 57, 58

INS Inertial Navigation System. 4

IoT Internet of Things. 10

ITS Intelligent Transportation System. 11

KF Kalman Filter. i, 29–31, 35, 42, 53

KPI Key Performance Indicator. 4

LOS Line-Of-Sight. i, iii

LTE Long Term Evolution. 4, 17, 18

MatLab Matrix Laboratory. 12, 22, 32, 33, 36

MIMO Multiple-Input Multiple-Output. 11

mMTC Massive Machine Type Communication. 9

mmWave millimeter Wave. 11

NCA Nearly Constant Acceleration. 27, 44, 46, 48

NCV Nearly Constant Velocity. 25, 28, 33, 44, 46, 48

NR New Radio. 1, 6, 11, 17, 19, 53, 57

OFDM Orthogonal Frequency Division Multiplexing. 21

PPP Precise Point Positioning. 4

PRS Positioning Reference Signal. 6, 17

RD Research and Development. 1

RSS Received Signal Strength. 10, 11

RTK Real Time Kinematic. 2–4

SBAS Satellite-Based Augmentation System. 3, 4

SCS Subcarrier Spacing. 17

TDoA Time Difference of Arrival. i, iii, 14, 36

ToA Time of Arrival. 10, 12–15, 57

TPM Transition Probability Matrix. 34

UE User Equipment. 2, 15, 32, 34, 57

UKF Unscented Kalman Filter. 12, 32, 33, 43, 45, 47, 49, 51, 54, 57, 58

URLLC Ultra Reliable and Low Latency Communications. 9, 10

UWB Ultra WideBand. 17, 21, 41

V2I Vehicle-To-Infrastructure. 1

V2V Vehicle-To-Vehicle. i, iii, 1, 9

V2X Vehicle-To-Everything. i, 2, 4