# DELIVERABLE D3.1

## TECHNOLOGY CONCEPT AND TECHNICAL REQUIREMENTS, SCENARIOS AND KPIS

MAY 31, 2023

**MARIOS RASPOPOULOS, STELIOS IOANNOU, ANDREY SESYUK**
INTERDISCIPLINARY SCIENCE PROMOTION & INNOVATIVE RESEARCH EXPLORATION (INSPIRE)

Co-funded by the European Union

Republic of Cyprus

RESEARCH & INNOVATION FOUNDATION

*"This work was co-funded by the European Union under the programme of social cohesion "THALIA 2021-2027", through Research and Innovation Foundation (Project: CONCEPT/0722/0031)".*

## Abstract

This report describes the concept, requirements and specifications of the technologies investigated in the project as well as the use case scenarios and the respective KPIs for the validation and verification of the system components and prototypes

# Table of Contents

# 1 Concept and Objectives

## 1.1 Current State of the Art

Location-based services (LBS) are playing a critical role in our life for many years now, the most characteristic example being automotive navigation. While initially the need was for outdoor localization, very quickly this need has expanded in indoor or more generally in satellite-obstructed environments, where GNSS typically fail. There has been significant work reported in the literature [1] over the last 20-30 years which includes many solutions and approaches for solving the localization problem in satellite-denied environments using - over the years - the current available radio technologies, however none of these solutions has ever been standardized as the universal solution (like GNSS for outdoor) for this kind of environments. Someone could find various reasons for this, like the incremental need for more and more accuracy, the rapid evolution of wireless (and other) technologies that facilitate the support of this higher accuracy which makes the adoption of one system unreasonable if it is going to become obsolete soon, the cost and maturity of the underlying technologies to be integrated in mobile devices, etc. Moreover, localization accuracy is relatively subject to the application used. For instance, typical GPS-level accuracy (3-10m) would be sufficient for automobile navigation, room-level accuracy (2-4m) would be enough to identify the presence of someone in a room or area of an indoor environment. Nevertheless, modern smart applications and systems have imposed finer position accuracy requirements going down to sub-meter-level and in some very sophisticated applications down to cm-level accuracy. Literature reports many works for achieving meter-level accuracy [2, 1]. Most of these works adopt a geometric approach to estimate the location by typically utilizing radio-related context like the Received Signal Strength (RSS), the Time of Arrival (ToA), the Time Difference of Arrival (TDoA) and the Angle of Arrival (AoA). The accuracy of the estimated position is however subject to the accuracy of these signal parameters which depend on the characteristics of the underlying radio technology and most importantly on the bandwidth, the frequency, and the power of the transmission. Wider bandwidths allow for better resolution in the time domain and hence more accurate time resolution and thereafter more precise range and angle estimates to be measured which is then translated into a better positioning accuracy. The recent evolution of Ultra-Wideband (UWB) technology in conjunction with its deployment in modern smart devices made it attractive for reaching submeter-level accuracy and many works have already been reported in the literature. The wide bandwidth, although it becomes beneficial in terms of positioning accuracy, it limits the transmitted power and effectively the range and spatial coverage of UWB systems. For this reason, UWB has been established as the most suitable solution to provide sub-meter level accuracy only in open non-obstructed environments. The need is now shifting also towards obstructed environments and the accuracy requirement is going in some cases down to cm-level. In this context **mmWave technology appears to be a more attractive option**.

Millimetre-wave (mmWave) is defining a new era in modern wireless communication by providing very wide bandwidths. This technology is currently used in some Wi-Fi systems (e.g., IEEE802.11ad) and is planned to be used in 5G and 5G-beyond communications in the near future as the it offers much more flexibility to use wider bandwidths and hence have the strong potential in achieving much higher data rates and capacity. mmWave systems typically operate in the frequency range between 30 to 300 GHz. The first standardized consumer radios were in the 60-GHz unlicensed band, i.e., 57–64 GHz, where 2-GHz signal bandwidth is typical in applications. The very large availability of bandwidth, together with the ease to use massive phase array antennas that allow the estimation of the azimuth and elevation angle can be used for **achieving 3D cm-level accuracy or better** [3]. Additionally, mmWave systems have higher transmit power allowance compared to UWB systems which compensates partly the high path losses typically experienced at high frequencies. The authors of [4] propose a multipath-assisted localization (MAL) model based on mmWave radar to perform indoor localization. The model considers the multipath effect when describing the characteristics of the reflected signal and precisely locates the target position by using the MAL area formed by the reflected signal. Experiments show that the model achieves a 3D positioning accuracy within 15cm. Also, the authors of [5] have demonstrated the benefits of array antennas towards identifying the orientation of the device. Although their work goes back to 2016, it is the very small wavelength at mmWave frequencies that facilitates the development of reasonably sized phased arrays that could aid the localization process by providing accurate angular information in 3D. Finally, due to this high sensitivity of the mmWave technology, positioning accuracy seems to be strongly correlated with the distance away from the target to be positioned. Positioning research using this mmWave technology is still on very early stages but early findings demonstrate its strong potential towards achieving the very high accuracy required by modern smart applications. The project aims to contribute towards these efforts by proving experimentally this concept and investigate the difficulties and challenges that need to be tackled.

Moreover, while, most of the **works reported in literature focus in 2D**, nowadays, smart applications have a 3D nature requiring the position to be estimated also in the z-dimension, **making the need for 3D positioning even more predominant**. Due to this, there is a growing research interest and activity during the last few years to develop/investigate positioning solutions in 3D. For example, the authors of [6] present a practical 3D position estimation method using an ankle-mounted sensing device, consisting of inertial measurement units (IMUs) and a barometer. Another work in [7] reports a 3D localization method for unmanned aerial vehicles (UAV) based on binocular stereovision technology is proposed.

It is evident that accurate localization systems are expected to play a pivotal role in the next generation of ICT technologies therefore it is a necessity to exploit the capabilities of mmWave technology towards achieving the desired accuracy. The 3D nature of the emerging applications also requires that this investigation is done in 3D.

Therefore, the project <u>**aims to proof the applicability of mmWave towards achieving cm-level 3D positioning accuracy**</u>.

## 1.2 Formulated Concept

For many years, the research community is actively pursuing more and more work towards improving the accuracy, reliability, efficiency, and performance of localization systems. As it turns out, the research focus is now turning towards developing techniques utilizing the most up to date wireless technology; **mmWave Communications**, for which literature reports a strong potential to achieve super-high precision going down to cm-level or better. The focus is also shifting in 3D positioning as classical 2D methods are not always enough to support the 3D nature of todays' smart applications.

The 5G new radio (NR) has had a successful worldwide release in 2020. After a few years, most of the world has already adapted to this communication standard while research clusters have been formed discussing already the next generation of wireless systems, termed 6G. Wireless networks are frequently praised only for their communication capabilities, while their inherent positioning and sensing benefits may be disregarded. In this sense, the 5G NR access interface, with its high carrier frequency, large bandwidth, and massive antenna array, provides excellent prospects for precise localization and sensing systems. Furthermore, 6G systems will accelerate the transition to even higher frequency operation, such as mmWave, as well as significantly wider bandwidths. In the 5G evolution to 6G, connectivity remains one of the most significant enablers of new services, but monetization of private networks requires more than simply a wireless connection. Also, 6G systems built for communication, sensing, and localization will likely enable new applications and services while improving traditional connectivity [8, 9]. Future trends in wireless communication indicate that 6G radios are likely to use signals at the mmWave range and have channel bandwidths which are at least five times wider than 5G. From a localization and sensing perspective this has multiple benefits [10]: (1) there is a more direct relation between the propagation paths and the environment as the signals on these frequencies do not typically penetrate walls, (2) the very fine time resolution of the power delay on these wide channels facilitates the resolvability of multi-path components to more accurately estimate ranges (3) smaller wavelengths that mean smaller antennas, especially phased array antennas that facilitate the good estimation of azimuth and elevation angles and hence facilitate accurate 3D positioning.

It is evident that 6G communication opens and new range of challenges and opportunities in localization and sensing which the authors of [10] summarize in 5 key research questions: (1) How can cm-level 3D positioning/sensing accuracy be achieved by utilizing the range of technologies used in 6G, (2) How can novel waveform designs be devised to better facilitate localization and sensing in addition to providing the fundamental communication benefits. (3) how can energy efficiency, high positioning/sensing accuracy and (we also say) low cost be supported in very high frequency and very highly mobile and dynamic environment in 6G systems (4) can real-time energy efficient AI/ML algorithms be used to further facilitate and support the localization and sensing process (5) how can the quality and accuracy between active and passing sensing be bridged. <u>We will be mostly focusing on the 1st and 3rd research questions.</u>

## 1.3 Aims and Objectives

### *1.3.1 Aim*

Following the research trends in positioning, we consider mmWave technology as the positioning-technology of the near future therefore the project aim lies on the following:

*To contribute towards the on-going research efforts on **cm-level positioning accuracy** by utilizing technologies that are expected to be integrated in future smart devices like **mmWave** and **array antenna technologies**. The project aims to investigate new techniques for achieving this 3D super-high accuracy and explore the limitations and challenges that need to be faced when using this technology especially due to the increased path-losses and signal variations on those very high frequencies. This is undoubtably a key contribution to the current knowledge as there are not many works in the literature on this accuracy-level yet. The main aim is to demonstrate the feasibility of this technology to satisfy the strong commercial need for 3D high precision position information.*

### *1.3.1 Technical Objectives and Operational Requirements*

The specific scientific and technical objectives set in the project proposal to meet the above aim are:

TO1) **Achieve cm-level positioning accuracy by designing and developing 3D positioning techniques using mmWave technology. This involves the development of**

TO2) **Develop Datasets and a Toolbox of Positioning Building Blocks**. This relates to the performing of measurements and simulations using mmWave technology to create datasets which will form the preliminary input and will facilitate the development of 3D positioning techniques. This also includes the **development of geometric methods** that will constitute the main building blocks towards the development of the various positioning techniques.

TO3) **Validate through measurements and assess the performance of the developed 3D positioning techniques.** This includes the setting up of experiments according to pre-defined scenarios to validate the developed techniques and assess their performance against set KPIs as well as the applicability of the mmWave technology to be used in commercial products and services.

For the above technical/scientific objectives to be achieved the following operational requirements have been set:

**OR1)** Acquire different types of mmWave Sensors and evaluate their performance in terms the following parameters and conditions by carrying out various in-situ measurements:

a. Ranging Precision – How accurately they measure the range to a target at different orientations.

b. Angling precision – How accurately they measure azimuth (and possibly elevation) at different ranges

c. Implementation Challenges – What kind of challenges they present when integrated into a system that comprises of multiple sensors.

**OR2)** Setup up a positioning testbed (prototype) comprising of a variety of mm-Wave sensors to collect positioning related context which can then be used to test various 3D positioning algorithms. For this, various targets can be used like drones, balls, humans etc.

**OR3)** Implement 3D Positioning algorithms in either MATLAB or Python.

**OR4)** Implement Kalman Filters to fuse mmWave data with context received from Inertial Measurement Units (IMU). This requires the integration of an IMU on a drone and the remote sending of this data to a central unit for filtering and fusing mmWave context.

**OR5)** Evaluate what would be the best way of managing and storing the received context. Either through MATLAB data structures, SQL datafiles or text/binary files and implement the necessary functionality for this.

**OR6)** Use simulations to generate positioning-related data to test the implemented algorithms and conduct sensitivity-analysis of the implemented 3D positioning algorithms but introducing uncertainty/errors on the received measurements. This will define the accuracy and robustness of the positioning algorithms in terms of increasing errors in the measurements.

# 2 Use Cases and Scenarios

A few measurement and simulation scenarios have been defined for the operational requirements and technical objectives of the project described in section 1.3.1 to be met.

Measurement scenarios include 3 types of scenarios (indoor cluttered – single target, indoor open-space single target, indoor open-space multitarget) and different mobility use cases for each. For all the environments Static measurements are going to be conducted in order to access the angle and ranging precision at different orientations and distances respectively and will be used to test the accuracy of the geometric 3D positioning models. It is worth noting that the output of the precision analysis (ranging error) will form the input to the Kalman filters which will be used in the mobility use-cases.

The mobility use-cases are intended to be implemented to demonstrate accuracy of the 3D positioning system when context from mmWave sensors is fussed with context from IMU with use of various types of Kalman Filters. For the indoor cases, only low mobility will be considered which involves the target (preferably drone, but also balls and humans will be considered) moving at low pedestrian-level speeds typically between 0.6-1.4m/s. For the outdoor case we will also consider a use case of high mobility with the speed of the target set up to 20m/s (depending on the drone capability). For all the only one target will be used in the environment and visual AI will be optionally used if time allows it.

Simulation scenarios will used also to assess the sensitivity of the implemented methods under various uncertainties. They will form an easy way to generate much location-specific data (ranges, angles) and introduce to it different levels of uncertainties/inaccuracies according to the precision analysis that will conducted in the static uses cases. Simulations will be carried out in MATLAB. For a set of measurement sensors deployed at pre-defined locations in an environment, distance and angle measurements will be simulated along predefined target trajectories and error will be statistically added to the measurements based on the statistics extracted from the precision analysis performed after conducting the measurements in the scenarios described above. Static cases will be mostly considered but (optionally if time allows it) will consider mobility cases although this was not included in the proposal.

### *2.1.1 Indoor Cluttered – Single Target*

| | Static Case | Low Mobility (optional) |
|---|---|---|
| Environment | Indoor | |
| Environment Dimensions (8pprox..) | 50-60 $m^2$ | |
| Clutter | HIGH – Consisting of benches, equipment on the benches, many metallic surfaces spread around the room | |
| Clutter Mobility | Stationary | Stationary |
| Number of Sensors | Up to 5 | |
| Target Mobility | Stationary | Pedestrian-Level (0.6-1.4m/s) |
| Number of Targets | 1 | 1 |
| Kalman Filtering | No | Yes |
| Targets | Drones and/or Balls and/or Humans | |
| 3D Positioning | Yes | |
| Sensors | mmWave, | mmWave |
| Applicability/Investigations | For precision analysis and preliminary 3D positioning using geometric methods without fusing it with data from IMUs | For 3D positioning using data from both mmWave and IMUs |
| Parameters to Measure | • Distance from Sensors<br>• AoD from Sensors. (mostly azimuth but also elevation if the sensors support it) | • Distance from Sensors<br>• AoD from Sensors. (mostly azimuth but also elevation if the sensors support it)<br>• IMU Data (Accelerometer [x,y,z], gyroscope [x,y,z] and magnetometer [x,y,z] |
| Evaluation Method | • Practical | • Simulation |

### 2.1.2 *Indoor Open space – Single Target*

| | Static Case | Low Mobility (optional) |
|---|---|---|
| Environment | Indoor | |
| Environment Dimensions (approx.) | 50-60 $m^2$ | |
| Clutter | Low – Consisting of desks and chairs. No metallic surfaces | |
| Clutter Mobility | Stationary | Stationary |
| Number of Sensors | Up to 5 | |
| Target Mobility | Stationary | Pedestrian-Level (0.6-1.4m/s) |
| Number of Targets | 1 | 1 |
| Kalman Filtering | No | Yes |
| Targets | Drones and/or Balls and/or Humans | |
| 3D Positioning | Yes | |
| Sensors | mmWave, | mmWave, IMU |
| Applicability/Investigations | For precision analysis and preliminary 3D positioning using geometric methods without fusing it with data from IMUs | For 3D positioning using data from both mmWave and IMUs |
| Parameters to Measure | • Distance from Sensors<br>• AoD from Sensors. (mostly azimuth but also elevation if the sensors support it) | • Distance from Sensors<br>• AoD from Sensors. (mostly azimuth but also elevation if the sensors support it)<br>• IMU Data (Accelerometer [x,y,z], gyroscope [x,y,z] and magnetometer [x,y,z] |
| Evaluation Method | • Practical | • Simulation |

### 2.1.3 *Indoor Open space – Multiple Targets*

| | Static Case |
|---|---|
| Environment | Indoor |
| Environment Dimensions (approx.) | 50-60 $m^2$ |
| Clutter | Low – Consisting of desks and chairs. No metallic surfaces |
| Clutter Mobility | Stationary |
| Number of Sensors | Up to 5 |
| Target Mobility | Stationary |
| Number of Targets | 5 |
| Kalman Filtering | No |
| Targets | Drones and/or Balls and/or Humans |
| 3D Positioning | Yes |
| Sensors | mmWave, |
| Applicability/Investigations | For precision analysis and preliminary 3D positioning using geometric methods without fusing it with data from IMUs |
| Parameters to Measure | • Distance from Sensors<br>• AoD from Sensors. (mostly azimuth but also elevation if the sensors support it) |
| Evaluation Method | • Practical |

# 3 Metrics/Key Performance Indicators and targets

To assess the performance of the mmWave Sensors and thereafter the accuracy of the developed 3D positioning algorithms the following metrics/KPIs have been set together with their target values. The target values have been selected based on what is currently reported in the literature but also in conjunction with the maximum dimension of the target to be detected.

## 3.1 Precision Analysis KPIs

For the precision analysis the actual error between the true value and the measured value will be recorded for both the ranging measurement and the angle measurements. This means that this error can either be positive or negative. For every measurement $i$ the error can be calculated as follows

$$Error_i = True\ Value_i - Measured\ Value_i$$

To estimate the average error of the measurement, only positive values will be considered. In this respect we will calculate two metrics. These are the average absolute error and the mean squared error calculated using the following equations for m measurements

$$Average\ Absolute\ Error = \frac{1}{m}\sum_{i=1}^{m}|Error_i|$$

$$RMS\ ERror = \frac{1}{m}\sum_{i=1}^{m} {Error_i}^2$$

## 3.2 3D Positioning Analysis KPIs

For the 3D positioning analysis, the most important performance parameter is distance error from the true value. This is the Euclidean distance between the ground truth 3D points and the one estimated by the positioning algorithm.

Given that:

$$True\ Location\ (Ground\ truth) = [x_T \quad y_T \quad z_T]$$

$$Estimated\ Location = [x_P \quad y_P \quad z_P]$$

The distance error for a single estimation is estimated as follows:

$$3D\ Error_i = \sqrt{(x_T - x_P)^2 + (y_T - y_P)^2 + (z_T - z_P)^2}$$

The average absolute error and RMS error can be estimated using the two equations above.

As it is also important to access the error in each axis the following errors need to be estimated

$$\Delta x_i = x_{T_i} - x_{P_i}$$

$$\Delta y_i = y_i - y_{P_i}$$

$$\Delta z_i = z_{T_i} - z_{P_i}$$

Likewise the average absolute error and RMS error can be estimated using the two equations above.

# 4 Technical Specifications

Considering the technical objectives, operational requirements, use cases and scenarios described above the following equipment is needed:

## 4.1 Hardware

| Type | Model Options | Quantity |
|---|---|---|
| mmWave Sensors | Texas Instruments IWR1642BOOST | 5 |
| | Texas Instruments IWR1843BOOST | |
| | Infineon DISTANCE2GOL | |
| Drone | DJI Air 2S | 1 |
| | Any other custom-built drone | |
| IMU | 9DOF IMU - 9250 | 2 |
| Cameras (optional) | Open CV AI Camera OAK-D | 5 |
| Microcontrollers | Raspberry Pi4 | 5 |
| | ESP32 with Wifi Connection | 2 |
| Laptop Computer | Any Windows Based Computer | 1 |
| Desktop Computer | Any Windows Based Computer | 1 |
| USB-3 to USB-c cables | At least 5 meters to | 5 |
| Power Banks to power the microcontrollers | USB output | 8 |
| UPS for the central desktop PC | Any | 1 |

## 4.2 Software

The following software tools will be needed:

- MATLAB
- Python
- Arduino IDE
- PyCharm or Visual Studio Code
- SQL Server Express

# 5 References


[1] F. Zafari, A. Gkelias and K. Leung, “A Survey of Indoor Localization Systems and Technologies,” *IEEE Communications Surveys & Tutorials,* vol. 21, no. 3, pp. 2568-2599, 2019.

[2] C. Laoudias, A. Moreira, S. Kim, S. Lee, A. Wirola and C. Fischione, “A Survey of Enabling Technologies for Network Localization, Tracking, and Navigation,” *IEEE Communications Surveys & Tutorials,* vol. 20, no. 4, pp. 3607-3644, 2018.

[3] D. Wang, M. Fattouche and X. Zhan, “Pursuance of mm-Level Accuracy: Ranging and Positioning in mmWave Systems,” *IEEE Systems Journal,* vol. 13, no. 2, pp. 1169-1180, 2019.

[4] Hao, Z; et. al, “Millimetre-wave radar localization using indoor multipath effect,,” *Sensors,* vol. 22, p. 5671, 2022.

[5] Y. Han, Y. Shen, X. Zhang, M. Z. Win and H. Meng, “ "Performance Limits and Geometric Properties of Array Localization," in IEEE Transactions on Information Theory, vol. 62, no. 2, pp. 1054-1075, Feb. 2016, doi: 10.1109/TIT.2015.2511778.”.

[6] Y. Zhao, J. C. Y. Liang, X. Sha and W. Li, “Adaptive 3D Position Estimation of Pedestrians by Wearing One Ankle Sensor,” *IEEE Sensors Journa,* vol. 20, no. 19, pp. 11642-11651, 2020.

[7] S. Yu and e. Al., “A Low-Complexity Autonomous 3D Localization Method for Unmanned Aerial Vehicles by Binocular Stereovision Technology,” in *10th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC),* , 2018.

[8] Saily, M; et. al, “Positioning technology trends and solutions toward 6g,” in *IEEE 32nd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*, 2021.

[9] T, Wild; et. al, ““Joint design of communication and sensing for beyond 5g and 6g systems,” *IEEE Access,* vol. 9, no. 30, pp. 845-857, 2021.

[10] A. Bourdoux; et al., “6g white paper on localization and sensing,” 2020. [Online]. Available: https://arxiv.org/abs/2006.01779. [Accessed May 2023].