FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Robot Localization in an Agricultural Environment

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Resumo

Localização e Mapeamento de robôs autónomos em ambientes complexos e instáveis, como uma vinha montanhosa, tem geralmente associadas algumas limitações de implementação. A comumente utilizada Navegação Estimada (Dead Reckoning) pode falhar devido às condições do terreno assim como o Global Position System (GPS) que nem sempre é fiável devido a ruído ou falhas de sinal. Particularmente, estas falhas são facilmente observáveis em meios agrícolas. Estes têm vindo a receber bastante interesesse nos últimos anos devido ao recente crescimento de sistemas de agricultura de precisão, nomeadamente sistemas de monitorização avançada em redes de sensores sem fios. Este tipo de sensores podem ser instalados em áreas de colheita por exemplo, e utilizados como marcadores de referência para localização robótica.

Neste trabalho, a performance do Pozyx, uma solução de localização baseada em Tempo de Voo com comunicação em Banda Ultra Larga é avaliada e implementada no AgRob V16, um robô agrícola de pesquisa científica desenvolvido pelo INESC TEC. Primeiramente, o erro tanto do sistema de medição de distâncias como do algoritmo de localização é caracterizado, formulando bases para a implementação de um filtro de estimação. O Filtro de Kalman Estendido é aplicado para a fusão de medidas do sensor com os dados da odometria do robô, estimando uma posição e uma orientação.

Os resultados obtidos são comparados com o algoritmo nativo do Pozyx bem como com outras implementações anteriores, mostrando a fiabilidade da tecnologia de Banda Ultra Larga para este tipo de sistemas. Para além disso, o sistema mostra ser uma alternativa para aumentar a redundância da localização necessária em sistemas complexos e sem acesso a GPS.

Abstract

Localization and Mapping of autonomous robots in an harsh and unstable environment such as a steep slope vineyard is a challenging research topic. The commonly used Dead Reckoning systems can fail due to the harsh conditions of the terrain and the accurate Global Position System can be considerably noisy or not always available.

More specifically, agricultural environments, which have received increased attention lately, can suffer from most of these constraints. Agriculture is moving towards a precision agriculture, with advanced monitoring systems and wireless sensors networks. These systems and wireless sensors are installed in the crop field and can be considered relevant landmarks for robot localization using different types of technologies.

In this work, the performance of Pozyx, a low cost Time-of-flight solution with Ultra-Wideband (UWB) technology, is studied and implemented on INESC TEC's AgRob, a R&D agricultural robot, through a beacon-based localization scheme. Firstly, the error of both the range-only system and the embedded localization algorithm of the sensor is characterized. Then the range measurements are filtered and fused with the Odometry values by an Extended Kalman Filter algorithm to output the robot pose and finally compared with the localization algorithm of the sensor.

The obtained results are presented and compared with previous works showing an increased redundancy of the robot localization estimation. The UWB is proved to offer a good solution for harsh environments, as the agricultural one, since its range-measurements are considerably robust to environmental conditions (until a certain point). The discussion also allows to present formulations for better results of Beacons Mapping Procedure (BMP) required for accurate and reliable localization systems.

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Thank you,

Teresa Conceição

*"In theory there is no difference between theory and practice.
In practice there is"*

Jan L. A. van de Snepscheut

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Abreviaturas e Símbolos

AOA	Angle of Arrival
BMP	Beacons Mapping Procedure
DGPS	Diferential Global Positioning System
EKF	Extended Kalman Filter
FCC	Federal Communications Commission
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
IMU	Inertial Measurement Unit
INESC TEC	Institute for Systems and Computer Engineering, Technology and Science
KF	Kalman Filter
LIDAR	Light Detection And Ranging
LOS	Line-Of-Sight
LSR	Laser Range Finder
MD	Mahalanobis' distance
MCL	Monte Carlo Localization
NLOS	Non-Line-Of-Sight
NOI	Node of Interes
PF	Particle Filter
PPP	Precision Point Positioning
PRF	Pulse Repetition Frequency
RBPF	Rao-Blackwellized Particle Filer
R&D	Research and Development
RBE	Recursive Bayesian Estimators
RSE	Recursive State Estimators
RFID	Radio-Frequency IDentification
RMSE	Root Mean Square Error
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RTK	Real Time Kinematic
SBAS	Satellite Based Augmentation System
SLAM	Simultaneous Localization and Mapping
STD	Standard Deviation
SOG	Sum of Gaussian
TDoA	Time Difference of Arrivel
ToF	Time of Flight
UAV	Unmanned Aerial Vehicle
UKF	Unscented Kalman Filter
UWB	Ultra-Wideband
ViTruDe	Vineyards Trunks and Masts Detector
VO	Visual Odometry
WLAN	Wireless Local Area Network
WO	Wheel Odometry

Chapter 1

Introduction

Localization and mapping are one of the key features of a truly autonomous robot application which must be aware of its environment in order to locate itself and navigate through its surroundings. Thrun, in his book "Probabilistic Robotics" [1], defines Mobile Robot Localization as "*the most basic perceptual problem in robotics*". Every robotic task is based upon the assumption of an intrinsically good knowledge of the location of the robot and the objects around. It is essentially the problem of determining the position and orientation (often referred as Pose) of the robot relative to a given map.

Although there are several accurate technologies for this purpose on regular stable conditions, the problem remains a difficult challenge when facing dynamic and complex environments. More specifically, robot localization in agricultural environments is a topic with an ongoing research interest, not only because of the growing industry of precision agriculture but also because of the severe conditions that a robot may face. The dense vegetation can cause signal blockage and multipath interference drastically reducing the efficiency of the widely used Global Positioning System (GPS). Visual perception systems can also fail due to weather conditions and not even the usually reliable dead reckoning systems can give an accurate localization since they also suffer from the harsh terrain shape. In this way, a reliable steep slope robot needs a redundant localization system which uses several sources of information to overcome all these issues.

This dissertation studies the implementation of an accurate system that aims to improve the redundancy of mobile localization in agricultural scenarios. Having system redundancy from different sources of information is extremely important especially to overcome GPS failures.

1.1 Context and Motivation

This work comes in the scope of AgRob, an Institute for Systems and Computer Engineering, Technology and Science (INESC TEC) robot, built for research and development of robotics in agriculture. AgRob is supposed to navigate through vineyards doing several different tasks like monitoring, trimming or harvesting. Most vineyards, especially those in the Douro Region, Portugal, are built on steep slope hills, a harsh environment for Robot Localization.

Different approaches have been studied by INESC TEC researchers in the past years. In [2], a redundant localization solution for mountain vineyards based on the identification of natural features by Laser Range Finder (LRF) measurements which can cope with the lack of access to Global Navigation Satellite System (GNSS) is presented. Trunks and masts were chosen as the natural features given their structured presence in each vineyard row and their visual detection procedure, ViTruDe - Vineyards Trunks and Masts Detector, was presented in [3].

Despite being a slight improvement, natural feature detection is still highly dependent on environmental conditions and was also proved to be less reliable on the row transitions of the vineyards since there are no vine masts or trunks on sight. Additionally, in [4], an artificial landmark mapping procedure is proposed, called Beacons Mapping Procedure (BMP). BMP can map automatically Radio Frequency Identification (RFID) tags that are placed in the begin/end of each vineyard row. All of the above are meant to be an input for our hybrid SLAM approach (VineSLAM) [2] in order to give redundant information. However, the implementation of ViTrude is still too slow for real-time use, so the current localization system only fuses LIDAR, odometry and *iBeacons*.

1.2 Thesis Outline and Objectives

Following these motivations, the main objectives of this thesis can be summarized as follows:

- Analyse different techniques and technologies for mobile robot localization and choose the best approach to deal with agricultural environments;
- Increase the redundancy of AgRob's localization and thus its robustness, safety and precision. The current localization system achieves precisions of around 30 cm, but a 10-20cm range is desired not only for safe and reliable navigation but also for more specific tasks involving the plants or grapes;
- Study the implementation of low-cost Time-Of-Flight (ToF) sensors for an accurate localization system.

Consequently, the work develops around a beacon-based localization system through the use of a low-cost ToF technology along with Ultra-Wideband (UWB) communication. Pozyx, the chosen positioning and ranging platform, is deeply characterized as a complementary alternative tool to the previous works on AgRob. The fusion of its ranges with Odometry values is considered by the means of an Extended Kalman Filter (EKF) and compared against Pozyx's own localization algorithm. The obtained results are presented and discussed and allow to present formulations for better results of accurate and reliable localization systems.

The structure of the thesis is organized in 4 major areas. Firstly, chapter 2 introduces the state of the art in robot localization with more emphasis on the agricultural case at the end. Chapter 3 explains our chosen approaches to deal with the problem and describes their theoretical implementation. Furthermore, in chapter 4, practical considerations of Pozyx and AgRob are explained and the methodology of experiments is described. Finally, the results of the tests are demonstrated and discussed in chapter 5 followed by some final conclusions and suggestions of future work in chapter 6.

Chapter 2

Background and Related Work

Mobile robot localization is one the key functionalities of a truly autonomous system and has been subject of a great research attention over the years. In order to successfully navigate, a robot must be completely aware of its position and orientation relative to the environment. Localization, however, can be a quite challenging process so choosing the right methods and technologies must take some factors into consideration. Among them, the following can be highlighted:

- Target application;
- Nature, dynamics and complexity of the environment;
- Device mobility;
- Communication and synchronization costs between system nodes
- Computational power and energy requirements
- Error and scalability requirements

In this chapter, an overview of the existing technologies and techniques for robot localization will be presented and explored, giving advantages, disadvantages and applications for each case. First, we describe non range-based sources of information followed by a more deep characterization of range-based localization, also defining different ranging and positioning methodologies. A special emphasis is given to the Ultra-Wideband case since it is the technology used in our implementation. In addition, filtering and fusion algorithms are analyzed in section 2.3 . Finally, we present the current state of the art of all the previously described approaches in the context of agricultural robots.

2.1 Non Range-Based Technologies

2.1.1 Dead Reckoning

Dead Reckoning uses wheel odometry (WO) information and the Inertial Measurement Unit (IMU) to integrate the position of the robot from wheel encoders and/or inertial sensors such as accelerometers and gyroscopes [5]. It processes the current state by fusing the previous determined position with changes in motion that occurred in the meantime. Although it is not a form of absolute localization, it is probably the most accessible form of position information. It is inexpensive and provides good short-term accuracy and high sampling rates. On the other hand, slippage and uneven terrains can be source of error when calculating the robot's motion. WO is also limited to wheeled ground vehicles and because it depends on previous measurements, the error will be cumulative over time which may also lead to divergences. Consequently, for outdoor complex environments and longer distances it should be fused with other sensors to keep the uncertainty bounded.

2.1.2 Visual Odometery

Visual Odometry (VO) acquires robot motion information from a single camera or stereo vision system. Despite requiring considerable more computational power, it can overcome some of the standard wheel odometry limitations like the inability to provide good information in irregular terrains. It is, however, still source of unbounded growth error since it estimates relative motion, highly dependent on previous measurements. Thus, like WO, VO should always be fused with another form of absolute localization technology.

It is not so commonly used as the other approaches but the growing popularity of evolutionary and learning algorithms have given this technique a lot of research attention lately.

One of the most important applications of VO are the non-standard robot locomotion systems like Unmanned Aerial Vehicles (UAVs) since they can not use standard wheel odometry [6] [7].

Mars exploration rovers, in GPS-denied environments, were other successful application of this technology [8]. The method was shown to be independent of terrain geometry and to outperform WO over longer periods of time. Additionally, fusion of standard dead reckoning with a monocular vision system also showed to accurately extract environment structure and robot localization [9].

2.2 Landmark and Beacon Based Localization

To get an absolute localization estimation is necessary to have absolute references in the world, usually called landmarks or beacons. A Wireless Sensor Network can be configured to be used as a localization system. In these approaches, typically the systems use reference points and its distances or angles to one or more Nodes of Interest (NOI) in order to estimate the required positions. These reference points are usually static either mapped a priori or with an unknown position which is dynamically determined.

An important notion is the difference between beacons and landmarks. The first term is usually employed for markers who once detected can yield immediately one or more coordinates. Conversely, using one beacon alone is not enough to have a proper position. They need to be used in a network of several beacons or use other types of information like angles from a compass. Artificial and natural landmarks are also differentiated in the literature. The first can simply be reflective markers but are often another type of sensor nodes. They have the shortcoming of requiring extra hardware components and more communication overhead whereas natural landmarks are already part of the robot's environment. On the other hand, the computational complexity for recognizing and mapping natural features is higher and not as reliable.

2.2.1 Ranging Techniques

Sensors measurements alone are not enough to localize a determined node so there is the need to come up with techniques to process ranging data to extract a position.

2.2.1.1 Received Signal Strength

Taking advantage of the fact that signal strength decays with distance, many sensors can estimate the distance to a node by the received signal strength indicator (RSSI). Empiric propagation models are explored to yield an estimated distance from the measured power of the received radio signal. Nevertheless, measuring this can be a tricky and noisy process by default. The directed signal is often attenuated and even damaged by multipath effects and signal reflections, commonly found in everyday environments. These factors may induce variations and noise into the measurements making it a not so reliable source of information. The RSSI is widely used in communications protocols like Bluetooth and WIFI [10]. It is an interesting solution for applications with power constraints or whose goal is to only get a feeling of proximity, i.e, applications where the presence of an object or how close is it to the user are enough information. However, for precise localization, it performs poorer than other techniques.

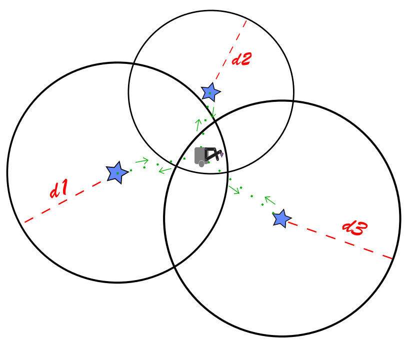
2.2.1.2 Time of Flight

Time of Flight (TOF) measures the travel time between the transmission and the reception of a signal. In its most simple form, the receiver can directly calculate the distance from the transmitter by multiplying the time of flight by the speed of propagation. This approach, however, assumes that the nodes are synchronized which is not always achievable due to system requirements. A two-way range methodology can cope with the lack of synchronization using only the knowledge of the turn-around time and the requester own clock. The distance is calculated by extracting the time that it takes to the signal to be sent by the transmitter, acknowledged in the receiver and mirrored back to the transmitter (round trip time). Without the necessity for synchronization, the distances from each node can be calculated independently making the overall system easily scalable. The main disadvantage of this method is that each node must act as a transmitter and receiver which can present some implementation challenges for some types of applications.

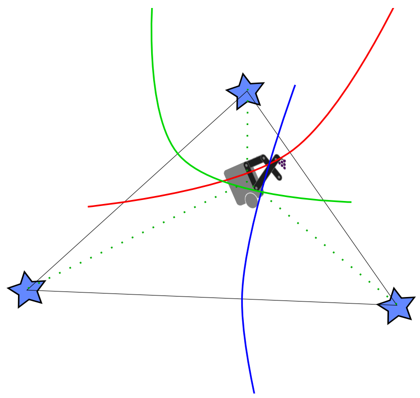
2.2.1.3 Time Difference of Arrival

In the presence of a partial-synchronized system, i.e there is no synchronization between the target and the reference nodes but there is synchronization among beacons, Time Difference of Arrival

(TDOA) can be used. This technique implies estimating the difference in the travel times between the NOI and two different reference beacons. In a TDOA operation, each pair of beacons will calculate the time of arrival of a periodical broadcasted signal and the desired distances can be induced. The communication operation between robot and beacons is in general simpler and more efficient than the TOF case. On the anchor side, however, there are a few major requirements that explain why TDOA, despite being efficient on the tag side, has not been widely implemented. The beacons need to be accurately synchronized with each other and in a continuously receiving mode which can be quite power-hungry. For this reason, ToF is usually preferred among the time-based methods since it is an accurate and more balanced implementation.



(a) Time of Flight



(b) Time Difference of Arrival

Figure 2.1: Ranging Techniques

2.2.2 Positioning Methods

Most common range-based positioning methods use either Trilateration/Multilateration (extract position from distances) or Triangulation (extract position from angles):

2.2.2.1 Trilateration

Trilateration is a localization method based on simple geometric concepts. Given a specific node and its distances to a number of references with known positions (they don't need to be fixed as long as their positions are certain), the unknown location and/or orientation can be determined. Each estimated distance will become the radius of a circle with the NOI as the center. Collecting at least 3 measurements from 3 non-collinear points, the intersection of the circles will output the desired position as depicted in Figure 2.1a. In theory, this intersection will be a single point. However, in the practical case, the measurements are subject to noise and uncertainty so this intersection will be in fact be a region of points. Different optimization algorithms can then be used to estimate the most probable position in this region. By increasing the number of beacons the uncertainty will inherently decrease. For a simpler explanation, the 2D case was used but in the presence of 3D positions, the principle is the same except the circles are spheres.

This scheme is the design base of GPS and often used for TOF and RSS positioning. TDOA, uses a similar concept called hyperbolic positioning (Figure 2.1b). A hyperbolic curve is determined by a constant difference between two points (the focus points). Since the references are now analyzed in pairs, each of these pairs will define a hyperbola and their intersection will output the desired position.

2.2.2.2 Triangulation

Triangulation uses geometric properties of triangles to estimate location. Given two absolute measured angles between the tag and two references and one known size (between the 2 references) a triangle can be exactly constructed and the NOI position determined using Angle of Arrival (AOA) techniques. Because the measured angles are absolute, it only needs 2 beacons to determine the localization. However, when only the relative angles between the NOI and the references are known a third reference point is required and a more general **3 Beacons Triangulation** technique is applied.

Angle of Arrival

The Angle of Arrival (AoA) estimates the angle of the transmitted wave when it reaches a receiving node provided with an aligned directional antenna array. Calculating the TDoA in each antenna of the array, the receiver can determine the signal's angle of incidence. Afterwards, with at least 2 angles from different receivers (for 3D needs at least 3) the position can be extracted using triangulation. This technique has the advantage of not requiring any synchronization between any devices since the time calculations are all done within the same node. However, its accuracy and precision are highly affected by multipath and by the distance between emitter and receiver[11]. Dealing with this requires relatively expensive hardware making AOA not a preferable solution for many robotic applications.

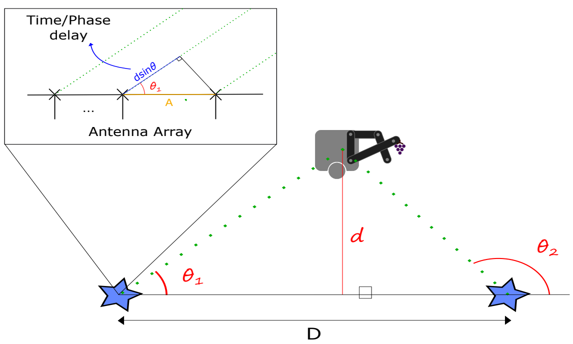


Figure 2.2: Angle of Arrival

2.2.3 Technologies

2.2.3.1 GPS

Global Position System (GPS) is a type of Range-Based technology based on satellite communication and the Global Navigation Satellite System (GNSS). GPS satellites broadcast a signal along with the exact time given by an atomic clock which is captured by a receiver on Earth. This receiver monitors multiple satellites and having at least 4 on sight, 3 for position estimation and 1 for clock deviation, the localization can be determined using trilateration/multilateration.

GPS is globally available for civilian use since the 1980's and consequently one of the most widely used localization systems. Although it is considered precise (within a couple of meters), it can be affected by some specific errors. Satellite clock errors, imperfect orbits, unmodeled delays in the Ionosphere and Troposphere and multipath reflections can all contribute to inaccuracies in the range measuring (Figure 2.3)

To overcome most of these issues, a group of more advanced technologies called "GPS Precision" were developed, namely **Differential Global Positioning System (DGPS)**, **Real Time Kinematic (RTK)**, **Satellite Based Augmentation System (SBAS)** and **Precision Point Positioning (PPP)**. Their basic concept relies on having a known fixed terrestrial station that can correct the final calculated position by the mobile receiver. This can improve the system accuracy to centimeter level by calibrating out the errors correlated to the user position (most of the previously mentioned except the multipath one). The specified technologies can differ in the system architecture, price, final accuracy, working range among others. For example, with DGPS and RTK, users have their own base station so a previous setup is often required. PPP and SBAS use a worldwide ground network reference which permits an "infinite" working range. On the other hand, their price is higher and the system operation can be a bit more complex. [12].

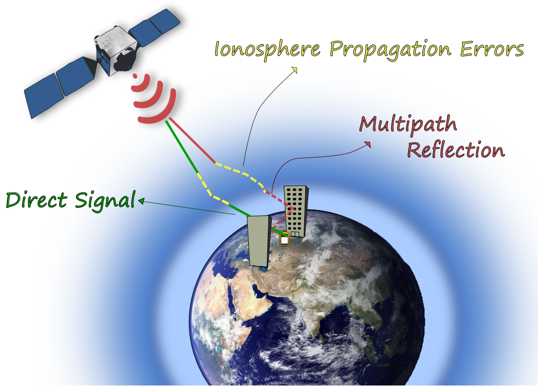


Figure 2.3: Multipath and Ionosphere Errors in GPS measurements

Both GPS and Precise GPS are used for many robotic localization systems as in [13], [14], [15] and [16]. However, in the presence of more complex environments, such as urban areas or indoors, it may be affected by GNSS signal blockage, attenuation or multipath interference. Furthermore, it has higher energy consumption and may need expensive hardware to achieve required accuracies.

Several different alternatives come then into the figure, that, in spite of not providing an "absolute position", can cope with some of the disadvantages of GPS.

2.2.3.2 Laser Range Finders

Laser range finders are devices that measure distances to objects using laser rays. They are widely used in robotic applications for localization given its high speed, accuracy and low complexity [17].

Even though for many robotic applications they are not the main source for localization they are almost always part of a robot structure because of its importance in mapping procedures. Contrary to other technologies later described in this section, laser range finders do not need the presence of extra hardware. They simply work by scanning the environment and matching different measurements to give a relative displacement and orientation.

Although this can be an advantage in terms of complexity and hardware costs it does require to have an accurate mapping procedure (usually in the form of 2D grid maps), either done a priori (offline) or simultaneously with the localization (online, generalizing to Simultaneous Localization and Mapping (SLAM)). Moreover, data association becomes also a concern since the measurements are not uniquely identified. To this extent, several works have been proposed in the cope of laser ranger finders which also cover the research on SLAM (see 2.3.3 for more details).

Self-localization along with detection and tracking of non-stationary objects has been implemented for both indoors [18] ,[19] ,[20] ,[21] and outdoors [22]. The accuracy of the pose estimation is shown to reach the cm level. Additionally, Laser range finders are often fused with other types of sensors to achieve an accurate localization [23], [24], [25].

2.2.3.3 Wireless Radio Sensors

WiFi, **Bluetooh** and **Radio Frequency Identification (RFID)** are some of the most used applications when working in a Wireless Local Area Network (WLAN), commonly an indoor environment [11]. For most of the cases, the first two work by inferring the user position based on the RSS, although other techniques may also be applied. There is no requirement for time synchronization between nodes in the network and the use of already existing infrastructures publicly available makes them a cheap and simple solution. On the other hand, as briefly stated in 2.2.1.1, RSS cannot be considered as highly reliable. Some studies propose spatial-temporal fingerprinting [26] or Gaussian Processes Classification [27] to cope with RSS inaccuracies but this is still an ongoing research topic.

Different implementations have shown an accuracy ranging from some decimeters until 3/5 meters [11]. With similar accuracies, WiFi distinguish itself for having higher data rate while Bluetooth has much lower power consumption. They have been successfully applied to robotic applications [28] , [29]. Their Fusion was also studied reducing error metrics up to 30% [30].

As far as the RFID is concern, its system is composed by a reader which uses electromagnetic fields to identify one or more tags. It has the advantage of being more accurate (cm level) and having a greater working range (up to 100 m for active tags) although the price of a RFID reader can be much significant than a single Bluetooth or WIFI transmitter (a single reader may cost up to $1500 [31]).

The information provided by RFID tags has lately been having a growing interest in robotic applications. Navigation, localization, mapping or object tracking are some of the tasks which it can help to solve. In [32], RFIDs tags on objects are tracked by a robot. Implementing a novel space partitioning optimization algorithm, RF-Compass, the system achieves a localization accuracy of 2.76cm. Mobile robot localization has also been solved by fusing RFID measurements with other sensors like sonars [33], laser range finders [34], [35] or stereo cameras [36].

2.2.3.4 Ultra-Wideband (UWB)

The **Ultra-Wideband** is also a wireless radio technology mostly used in communications which has been lately receiving more attention in positioning systems [37], [38]. Its first radar application dates back the 1960's but due to political and technological restrictions, for most of the 20th century was only used for military purposes. More recently, in 2002, the United States Federal Communications Commission (FCC) released 7.5GHz of unlicensed spectrum resulting in a deeper interest and usage flexibility by the general public.

Operational principle

UWB ranging works by sending an omnidirectional radio wave from one module to another and measure the time difference between its emission and reception (using one of the time-ranging methods). Since radio waves travel at approximately the speed of light [1] one can easily deduce the distance traveled. The times involved in UWB are particularly small, in the order of nanoseconds, so there is the need for a high timing accuracy which can only be achieved in the presence of a very narrow pulse. The Heisenberg's principle (2.1) deduces the bandwidth (Δf) need for a given signal pulse width (Δt). By using a large range of frequencies and consequently a very narrow pulse, the signal's peak can be accurately measured and reflections can be avoided.

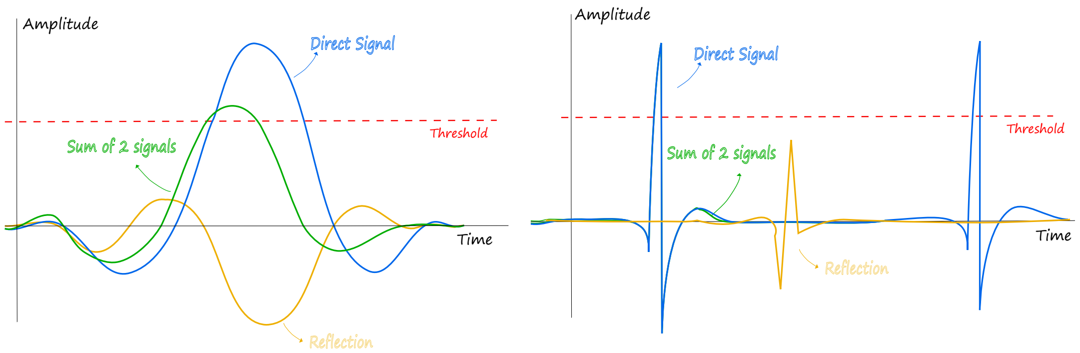
$$\Delta t \Delta f \geq \frac{1}{4\pi} \tag{2.1}$$

Exemplifying, with a Δf = 20Mhz the resulting pulse-width will be no smaller than 4 ns and consequently around 1.2 m long. This means that any reflected signal from an obstruction until 1.2 m will overlap the Line-of-sight (LOS) direct pulse and decrease system accuracy. On the contrary, increasing Δf to 500MHz results in pulses of 0.16 ns wide and therefore different reflections at more than 5 cm can be easily resolved. For better illustration, the effects of narrow and wide bandwidth on pulse reflections are shown in Figure 2.4.

Moreover, even without multi-path issues, measuring the peak of wide pulses is not always an easy task and the noise filtering can be more difficult.

[1] slightly smaller than the actual speed of light in vacuum because of air temperature, and pressure

The higher bandwidth comes at the cost of strict low power regulations for UWB systems (Figure 2.5). Because of this, a single pulse isn't distinguishable from noise when it reaches the receiver. The solution comes by sending a train of pulses instead of just one, which will accumulate power and make the detection possible.



(a) Narrowbanded (b) Ultra-Wideband

Figure 2.4: Comparisson of Multipath in Narrow Bandwidth signals and in Ultra-Wideband signals

Localization Methods

In terms of localization methods, time-based schemes as TDOA and TOF are preferable for UWB since they explore the high time resolution given by large bandwidths. The use of AOA can be challenging due to a lot of different identified paths. Furthermore, the required antenna rays are expensive annulling the advantage of UWB low-cost transceivers. As for the RSS methods, although the very large bandwidths can present several improvements to their performance, they still come up short when compared to time-ranging methods [38].

Main advantages

This technology can be very useful to robot localization given its low cost and excellent time domain. Because of the increased radio spectrum bandwidth (>=500MHz) and sub-nanosecond duration pulses, it is not only robust to the interference of other types of Radio Frequency (RF) signals but can also discriminate the different multipath components of the received signal, solving the issues observed in the previously mentioned technologies. Moreover, the lower frequencies of the UWB spectrum can penetrate some variety of materials (like walls), making it particularly attractive for indoor applications. Generally, it can deliver for most applications a centimeter level accuracy (around 10 cm [39]) as opposed to more traditional narrow banded technologies, as WiFi and Bluetooth, which only have a meter level of accuracy.

Limitations and challenges

One of the drawbacks of UWB are the restrictions imposed by governmental regulations on the use of the power spectrum. These regulations may vary depending on country, therefore, the network parameters cannot be set homogeneously even for the same application. Apart from that, modeling a UWB channel can be challenging. Different frequency components usually present different interactions with the surrounding environment and antennas response is more variable, especially in terms of angular dependency [40].

Finally, as observed in different studies [40], [41],[42], time measurements variance in a Non-Line-of-Sight (NLOS) environment is usually much larger than in a Line-of-Sight one. In fact, TOF range based error can be modeled as a gaussian distribution in LOS but for the NLOS case, it also adds an exponentially distributed random variable [40]. This difference in system performances makes it harder to have a precise error characterization which can be essential for processing and filter the data in the best way possible for navigation systems. Although not always possible, statistically modeling the environment using a priori information can be employed as a solution. Practical tests proved that by identifying NLOS and LOS situations, the accuracy increased to at least a factor of 2.5 [40].

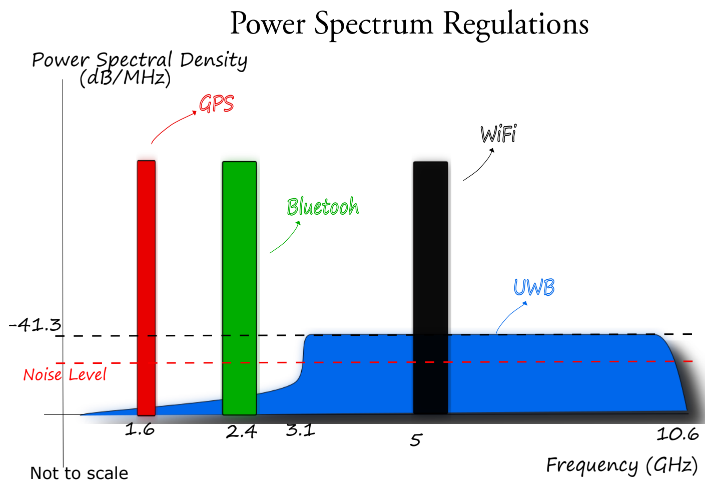


Figure 2.5: Emitting power regulations for unlicensed spectrum (FCC)

Applications and Previous Work

UWB systems have been an intensive research topic for the past decades. DecaWave using TOF [43], Ubisense which fuses AOA and TDOA [44], Sequitir with TDOA [45] and Time Domain [46] are the most known commercial implementation of the technology giving accuracies ranging from 10 to 15 cm. Some examples of these applications are ground penetrating radar [47], medical imaging [48], vehicular radar and military communications.

More recently, UWB found applications in robot localization. Most of the works explore the technology for indoor applications: [49] proposed a UWB-Infrared localization system along with

TDoA. [50] combines UWB range measurements with the vehicle odometry using a Particle Filter approach, analyzing UWB range errors for NLOS and LOS scenarios. Further characterization for a hybrid approach of indoors and outdoors is done in [51] where data from UWB and GPS are explored and fused by a Particle Filter. The same principal is applied by [52] for a quadcopter localization but using an EKF filter instead.

2.3 Fusion and Estimation Algorithms

In an ideal world all the above technologies can directly or indirectly infer the exact robot's position. However, in practice, there is uncertainty associated with such a task which can arise from different factors like the dynamism of the environment or sensor limitations such as resolution and noise. Consequently, the ability to cope with that is an important system requirement. Probabilistic algorithms are usually employed to help increasing the robustness and accuracy of the system with two main objectives:

1. Deal with sensors noise and ambiguous measurements, detecting unexpected interferences from the environment;

2. Fusion of different technologies. Although most of them can be used independently, proper fusion in a multi-sensor environment can increase the redundancy in the state estimation.

Despite the existence of other types of estimators (like batch estimators) the focus of this section will be on the **Recursive State Estimators (RSE)**, the most used in robotics. Those share a common representation of the system state x based on the Bayes Theorem (2.2) reason for which they are also called **Recursive Bayesian Estimators (RBE)**. $p(x|y)$, also known as posterior probability, represents the belief of the system being in the state x given the measured data y. In the case of localization, the state is the robot's pose but it can be set as a mixture of any other unknown variables to be predicted. Another side note is the reliance of the RSE on the Markov assumption. The premise states that past and future data are not dependent if the current state is known. As an implication, the knowledge of the immediately previous state and the current measurements is enough to predict the current state. Opposing to this sequential approach, batch techniques need to keep track of a history of observations [1].

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)} \tag{2.2}$$

2.3.1 Gaussian Filters

Gaussian filters are by far the most popular filter techniques in the state-of-art localization algorithms. The beliefs assume a well-known unimodal distribution - multivariate gaussian distribution – which can be simply characterized by a mean and a covariance. Despite some shortcomings, in many practical problems, gaussians are considered robust estimators. In this category, the highlights are the Kalman Filter and its extended versions.

2.3.1.1 Kalman Filter

The Kalman Filter [53] is one of the oldest and best studied techniques for implementing Bayesian inference in state filtering and prediction. Its particularity lies on the linearity of the state and measurement probabilities representation. Generally, the algorithm keeps track of the state's estimation and the uncertainty of this estimation in two different phases: **Prediction** and **Correction**. The first one predicts the new state by inputting the previous estimation and its uncertainty as well as the motion data into a state transition model. The latter integrates all the sensors data into the calculated state in the previous step and outputs a final estimation. The correction phase is, therefore, the step where all other sensors and technologies can also be fused. Apart from some fusion implementations [54], most real-world localization systems rarely fulfill the linearity constraint of the basic Kalman Filter so their application is reduced to the most trivial robotic problems. To overcome the linearity assumption an extension of the Kalman Filter, the Extended Kalman Filter (EKF) was created.

2.3.1.2 Extended Kalman Filter

The **Extended Kalman Filter** in its sense is the extension of the state transition and measurement models to non-linear functions. The state is still represented as a joint probability gaussian distribution over the variables, however, this probability is now only an approximation to the true belief and not the exact one. The key idea is to linearize the state around the current estimation by the first order Taylor Expansion (2.3) which is the source of the non-exact representation of the belief.

$$f(x) = f(a) + f'(a)(x - a) \tag{2.3}$$

EKF is without doubt the most popular tool for state estimation in robotics ([55], [56], [57], [58], [59]).

Its main advantages lie in its simplicity and computational efficiency due to the unimodal gaussian representations. The computational complexity is only dependent on the dimension of the measurement and state vectors and therefore is much more efficient than Non Parametric filters whose algorithms use larger and more complex representations of the world.

It is, however, based on two major assumptions. The first postulates that the state estimation is close enough to the real value since the system is linearized around the current prediction. The second one assumes that the non-linear functions can be accurately approximated. If the degree of nonlinearity is indeed not too high, EKF approximations are generally good and accurate. It is, in practice, extremely important to keep the uncertainty small, since by propagating the gaussian distribution through the linearized model, larger errors can be induced if the gaussian becomes too wide. Nevertheless, sometimes these functions are highly non-linear or even multi-modal (which cannot be represented by a gaussian distribution). In these cases, the EKF may perform poorly or not converge at all.

2.3.1.3 Unscented Kalman Filter

A more recent technique, the Unscented Kalman Filter (UKF), was proposed by Julier and Uhlman [60] to address the error caused by the linearization of the EKF. The state is still approximated as a gaussian random variable but is now only linearized in a minimal set of sampled points. The computational complexity is in the same order of magnitude as the EKF, although the process of selecting the sigma points entails slightly more effort. Furthermore, this process must be done carefully and cannot be generalized for every case.

Comparisons between EKF and UKF implementations were presented in [61], [62] and [63]. For strong nonlinearities in measurement models, UKF yield in general better performance but for the opposite case, they achieved similar results. A slightly different performance was exposed in [52], regarding an outdoor scenario for a quadcopter UWB localization system. EKF revealed more consistent results against UKF who showed some sensitivity to the weights of the sampled points in different anchor configurations. This proves that generally, if the models considered are reasonably stable EKF is simpler and reaches good levels of accuracy. On the contrary, if the models are highly non-linear, UKF is preferable.

2.3.2 Nonparametric Filters

Gaussian techniques tend to work well only if the position uncertainty is small. Even solving the approximation issues of the EKF, UKF doesn't attend for the case where the system dynamics cannot be approximated by a unimodal gaussian distribution neither can it process "negative information". The absence of a measurement can give relevant clues to the estimator but this negative information cannot be represented by gaussian beliefs. For this reason, Kalman Filter implementations simply ignore this fact.

A popular alternative is to remove the fixed distribution form of the beliefs representation, which is the key concept of nonparametric filters. Particularly, posteriors approximation is done by a finite number of values that will correspond to a specific region in the state space.

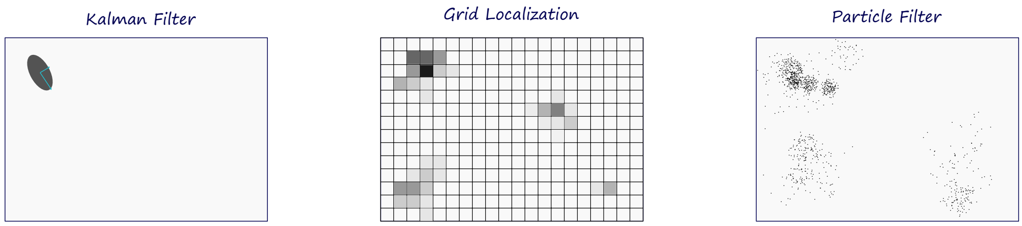
Compared to the gaussian filters, they are well-suited to deal with global uncertainty, data association problems and complex multimodal probability distributions. To a certain extent, they also don't make specific assumptions relatively to the initial state of the system and therefore can solve quite well the problem of global localization. These come with the expense of an increased computational cost which will depend on the number of parameters used for the beliefs approximation. Changing them will affect the quality of the technique (the more the merrier) so a trade-off analysis should be done taking into consideration the complexity of the posteriors.

2.3.2.1 Histogram Filters

Histogram filters are a class of nonparametric techniques that decomposes the state space into regions, assigning for each one a certain cumulative probability (histogram representation). The state belief is now represented by a probability density function and by choosing the "most likely sampled region" the estimation can be completed.

A common implementation of this filter is called **Grid Localization** or grid-based Markov localization [1]. The robot surroundings are discretized into a grid map with each cell representing the probability of the robot's location being there. With the right grid resolution, this technique can be a very good approach to the localization problem. This choice must be done carefully though: fine high-resolution grids can result in implausible slow algorithms and huge memory consumption whereas the discretization of the space into coarse grids may have negative performance outcomes.

Grid Localization has its main advantage on the robustness and ability to converge even in dense or unstructured environments. On the downside, its computational overhead can be prohibitive. One of the most promising solutions presented to overcome this, uses the oct-trees concept by dynamically redefining the grid size according to the robot's uncertainty [64].



(a) Kalman Filter (b) Grid Localization (c) Particle Filter

Figure 2.6: Different state representation in probabilistic localization algorithms

2.3.2.2 Particle Filter

Another common approach with a lot of popularity in robotics is the **Particle Filter (PF)** [65], [66], [67], [68].

The concept is similar to histogram filters also having an approximation of the state space by a number of parameters. However, the process itself and the distribution of the samples (called particles) is done differently.

In the mobile robot localization context, **Monte Carlo Localization (MCL)** [69] is the Particle Filter algorithm receiving more attention In MCL, each particle represents a possibility of the robot being at a determinate pose. The denser a region is, the more likely is it that the state falls into that region. The algorithm is vaguely divided into the following steps:

1. Initialization, in which a set of particles is randomly and uniformly distributed over the space.

2. Propagation of the particles, modeled in general by the robot's motion. New measurements assign non-uniform weights to the particle set.

3. Resampling process. As a result, the region around the truth robot's pose will, if everything goes well, be denser now and some of the particles with smaller weights will be removed. The new state is extracted by a weighted sum of some of the particles, usually only the ones in the densest region.

Compared to the basic grid-Markov localization it can reduce the memory requirements and the process requirements. It is also considered more accurate than the grid algorithm with a fixed cell size [69].

Drawbacks of the naive implementation of Monte Carlo localization occur mostly due to the resampling phase. An unlucky sequence of events can wipe out all particles near the true state. This issue is also known as particle deprivation and can induce the system in a state of "no possible recovery". One way of trying to mitigate the problem is by introducing random particles (noise) each step. Although it can add some extra final error, the algorithm is now more robust and more certainly to converge.

Practically, the accuracy of the filter is, like in the histogram filter, determined by the size of the particle set. Thus, the stated problems only tend to arise in high-dimensional spaces and when the number of particles is too small relative to all the regions with high likelihood.

2.3.3 Simultaneous Localization and Mapping

The localization stage of mobile robots is highly related to the mapping procedure. The previous algorithms work well for two localization scenarios:

1. The environment is previously mapped and the robot's pose is the variable to be determined

2. The robot's pose is known and the map needs to be constructed.

A third case, when the robot doesn't have access to neither the map nor its own position comes into the scope of a problem commonly referred as the Simultaneous Localization and Mapping. It is by far one the most researched problems in robotics [70], [71].

The earliest and most popular SLAM algorithm to be proposed is based on the EKF [72], [73] and has been successfully applied to a diverse number of robotic navigation applications [74], [75], [76], [77]. The main disadvantages of EKF SLAM are the complexity of the updating step and the limitation to relatively sparse maps with non-ambiguous landmarks. Other tools with different advantages and disadvantages have also been proposed and implemented. RGBD SLAM [78], FastSlam [79], Unscented FastSlam (UFastSlam) [80], Rao-Blackwellized Particle Filer RBPF-SLAM [81] [82] or the Sum of Gaussian (SOG) method [83] are among them. Given that SLAM is a far more complex problem than the single localization and falls away from the main implementation of the thesis it won't be further characterized.

2.4 Agricultural Robots

Autonomous robots have been a large engineer field for many areas. As their technology becomes more and more developed, specific applications like precise agriculture emerge [84], [85]. Robots are now revolutionizing a variety of different tasks in agricultural environments releasing farm workers from hard manual labor and addressing numerous challenges.

For example, due to vast fields, crops imply extensive monitoring which is usually a very low-efficiency task if done by humans. Introducing autonomous robots can not only help in seed planting and selective harvesting but also improve the analysis and control of the soil and products quality. Pruning [86], weeding [87] and spraying [88] are also other applications that can benefit from robotics.

Nevertheless, the situation is not entirely rosy. In most of the cases, these tasks require a great level of robustness in all their navigation, visual perception and manipulation tools. In the specific case of localization, dense vegetation can cause signal blockage and multipath interference of some of the previously mentioned technologies. Uneven and harsh terrains will also lead to enormous errors on the widely accepted dead reckoning systems. For this reason, this is a relevant and growing research interest by the robotics community.

Figure 2.7: Harvesting Robot

Figure 2.8: *Wall-Ye* [86] in a pruning task

2.4.1 Localization

One of the boosters of the commercialized agricultural robot was *BoniRob* developed by Bosch's Deepfield Labs [89]. Its main "online" source of localization is the IMU and wheel odometry. However, it navigates through a map done a priori through high precision GPS. While using RTK-GPS it achieves accuracies around 2 cm. Other than that the accuracies are in the sub-decimeter level [90].

More specific to the state of art in vineyard environments (like the one AgRob V16 will face) one can enhance *VineRobot* [91] and *VinBot* [92]. They are all-terrain autonomous robots able to monitor the grapes state by the means of several non-invasive technologies. Similar to *BoniRob*, *VinBot's* localization system involves a precision RTK-DGPS fused with IMU and wheel Odometry data.

The idea of using GPS for agricultural robots is not new. As a matter of fact, most of the literature proposes a fusion of high precision GPS, inertial measurements and wheel odometry. After that, using machine vision (stereo cameras or RGB-D cameras) and laser scanners they identify crop rows, trees and other obstacles to perform reliable navigation. Some examples of this are the *The Demeter System for Automated Harvesting* [93], created to plan and execute harvesting operation and Massey University's autonomous Kiwi-Fruit picking robot [94].

Also GPS-based is the general localization of *Bin-Dog* [95], a fruit bin carrier, and of *U-Go Robot* [96], a rough terrain outdoor vehicle, with the difference that they also address the case inside orchard's rows with dense vegetation (where GPS is not so reliable). For this case, relative measurements with laser and ultrasonic sensors are used.

The *Grape Project* [97] optimizes the fusion of the IMU,GPS and Odometry by a factor graph based filter. In addition, the system exploits a Light Detection And Ranging (LIDAR) sensor combined with a Monte Carlo Localization algorithm to localize the robot and to map the vineyard through SLAM.

Noguchi [15] presented an on-field navigation system with a vision sensor, a fiber optical gyroscope (FOG) and RTK-GPS, comparing the navigation with GPS-FOG only, Vision only and fusion of all. The results were satisfactory for the three cases (accuracy < 20 cm) with better performance for the fused system.

Most of these robots have shown to self-localize and navigate accurately. However, almost all of them rely on high precision GPS to do so. Some of the mentioned signal issues or simply their non-affordable price make GPS-free localization approaches an interesting research topic which has only been extensively explored in indoor environments.

Machine Vision, often used for perception and navigation among agricultural robots, places itself as one of the most popular alternatives. Sharifi explores in [98] the fusion of stereo visual odometry (SVO) with wheel odometry and IMU measurements for harsh agricultural scenarios. A neural-fuzzy machine learning algorithm is also proposed to deal with some accumulative drift of the SVO for large ranges. Other interesting solutions fuse vision with natural [99] or artificial landmarks [100] as an input to a SLAM framework. The landmarks approach is also considered together with 2D Range Lasers. From the range measurements of trees in a vineyard row, lines are extracted and provided as features to SLAM [101] or fused with artificial landmarks with an EKF filter [102]. As noted by the authors the 2D filter works well even for hilly terrains as long as the slope is not excessive. However they also note that it can be sensitive to the dead-reckoning errors so noise and errors should be modeled carefully.

The majority of works stated, address uneven but approximately flat terrains (in terms of altitude). Other kinds of vineyards, built on steep slope hills, are not so intensively mentioned in the literature. In a preceding work, INESC TEC researchers working with AgRob, implemented a similar approach to Marden [101] and Libby [102] but with a target environment of steep slope vineyards. A redundant localization solution based on the identification of natural features by Laser Range Finder (LRF) is tested in a simulated environment in [2]. Despite being a slight improvement, natural feature detection is still highly dependent on environmental conditions and was also proved to be less reliable on the row transitions of the vineyards since it has no vine masts or trunks on sight (the identified natural landmarks). Additionally, they extend their work in [4], with an artificial landmarking mapping procedure called Beacons Mapping Procedure. BMP can map automatically RFID tags that can be placed in the beginning/end of each vineyard row. These artificial beacons are an input to the EKF SLAM approach (VineSLAM) presented in the previous paper and stated as a redundant localization information for agricultural robots.

In sum, hard environments like steep slopes require a redundant localization system using several sources of information. This helps to overcome GPS/GNSS failures, high levels of odometry noise due to rocks and visual perception system failures due to weather conditions. In this thesis, we have chosen systems that can give distance measurements to beacons with the Time-of-Flight technology.

Chapter 3

Approach and Algorithms Developed

In this chapter, the implemented approaches will be exposed and their theoretical foundations explained. The formulation of the Beacon-Range Localization and its assumptions are described followed by a meticulous analysis of the EKF Localization algorithm implemented. Finally, in the last section, several considerations regarding the practical implementation of the algorithm are exposed.

3.1 Localization Methods and Technologies

Given the specifications of the problem previously depicted and after analyzing the different methods and solutions described in the literature review, a localization based on Ultra-Wideband beacons was chosen as the main approach. It is not only a reliable and robust solution for absolute positioning but is also able to cope with real-time measurements and usually not too expensive. Active beacons were preferred over natural or passive artificial landmarks because of their a higher working range and flexibility. This is particularly important in an outdoor environment removing the need of following specific paths to recognize landmarks and eliminating computational efforts of object recognition and data association.

Lastly, regarding the ranging technology, ultra-wideband appeared as an appealing solution to deal with the issues inherent to an environment like a mountain vineyard. Although it is still an on going research topic, its characteristics can help to overcome dead reckoning errors due to the harsh terrain, multipath effects of other radio technologies or GPS signal blockage. UWB communication is implemented in our system through Pozyx, a relatively low-cost commercial solution for accurate ranging and positioning, composed of one main sensor tag and 4 other sensors used as beacons (see chapter 4 for more details).

3.2 2D Beacon-Based Localization

Generally the problem of Robot Beacon-Based Localization can be defined as estimating the robot's pose $X = \begin{bmatrix} x & y & \theta \end{bmatrix}^T$ by measuring the distances and/or angles to a given number of beacons mapped in $M_B = [x_{Bi} y_{Bi}], i \in \{1 \ldots N_B\}$ both X and M_B defined in a global reference frame $GxGy$.

For this specific case, distance measurement, the following assumptions can be made:

- Although the absolute position relative to the Earth is tridimensional, the localization can be solved for the 2D case. It is assumed that the robot is navigating in a two dimensional plane, even in the presence of severe inclination.
- The beacons position is static and known a priori so M_B is clearly defined at all moments;
- At time step k the odometry values are available for $k \in \{0 \ldots k\}$. This will be used to provide the input $u(k) = \begin{bmatrix} \Delta x_{odom} & \Delta y_{odom} & \Delta \theta_{odom} \end{bmatrix}^T$ to the system in which each $u(k)$ refers to the variation of the odometry between times k and $k-1$.
- $Z_B(k) = \begin{bmatrix} r_{Bi} \end{bmatrix}$ specifies the measurement of the range sensor embedded in the robot to each beacon i at the instant k.

Our overall model of 2D localization given distances to beacons is illustrated in Figure 3.1.

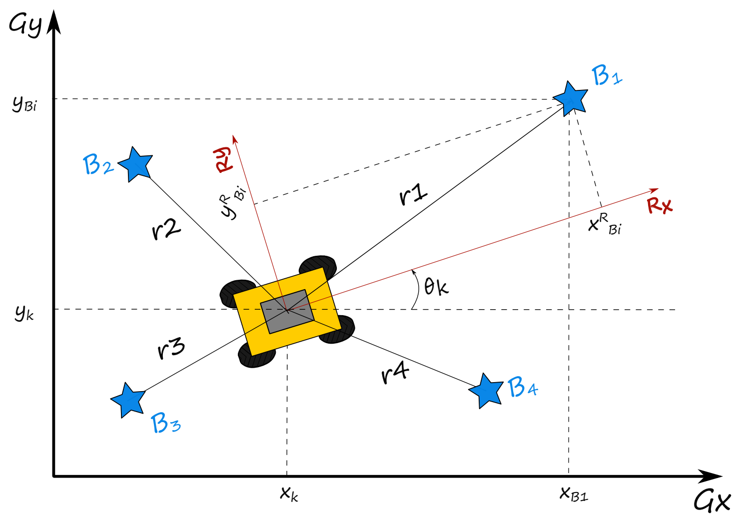


Figure 3.1: 2D Localization given measurements to beacons with known position

To solve the problem of 2D Beacon-Based Localization two approaches were compared:

1. Implementation of an Extended Kalman Filter localization algorithm for fusion of odometry values and raw range measurements from Pozyx;
2. Pozyx internal UWB-only positioning algorithm.

3.3 Implemented Algorithms

Raw range measurements of the beacons alone can't return any robot location, hence a localization algorithm has to be chosen. The well known EKF Localization was considered a good solution given the problem conditions.

It is of relatively simple implementation and low computational costs allowing a real-time localization output that can be important to, for example, path planning. Moreover, EKF is also a flexible and scalable fusion algorithm, therefore further data from other sensors, technologies or implementations can be added easily.

In this case, odometry data was fused with sensor range measurements. It is a particularly good combination because odometry provides accessible high-frequency information about the relative motion of the robot. On the other hand, sensor ranges can yield absolute information, independent from the past and its errors are not cumulative over time (as opposed to odometry). Since both sources are not correlated, they can balance each other pretty well.

3.3.1 Extended Kalman Filter

As previously mentioned, EKF is a filter algorithm often used for robot localization and sensor data fusion. As for all Kalman Filters, it models the robot's state as a gaussian distribution $X_k \sim N(\mu_{Xk}, \Sigma_{Xk})$, where μ_{Xk} is the robot's pose mean value and Σ_{Xk} the correspondent covariance matrix.

Before further implementations, it is important to define and understand the way the robot's state and the sensor observations evolve in time. The State Transition Model and the Observation Model will tell EKF's Prediction and Correction phases respectively how should they interpret the inputted data.

3.3.1.1 State Transition Model

The state transition model (3.1) is a probabilistic model that characterizes the state distribution over the inputs. In a robot localization problem, this model is also referred as a kinematic model since it defines the probability of the state given the robot's relative motion.

There are two main types of motion models that can define f: Velocity Models or Odometry Models. The first defines the next state as a function of rotational and translational velocity whereas the latter use odometry measurements instead. Odometry models are said to be more accurate than velocity ones but have the drawback of just being available after the actual robot motion. Although this is not a concern for filter algorithms, it may be a limitation for controlling purposes [1]. For now, the main concern is estimating the pose, so an Odometry Model was adopted (3.2), where the previous state X_k and the variation of odometry values u_{k+1} are given as inputs.

$$X_{k+1} = f(X_k, u_{k+1}) + N(0, Q) \tag{3.1}$$

$$f(X_k, u_{k+1}) = X_k + \begin{bmatrix} \Delta x_{Odom} cos(\theta_k + \frac{\Delta\theta_{odom}}{2}) - \Delta y_{Odom} sin(\theta_k + \frac{\Delta\theta_{odom}}{2}) \\ \Delta x_{Odom} sin(\theta_k + \frac{\Delta\theta_{odom}}{2}) + \Delta y_{Odom} cos(\theta_k + \frac{\Delta\theta_{odom}}{2}) \\ \Delta\theta_{odom} \end{bmatrix} \tag{3.2}$$

The chosen model was introduced by Eliazar [103] and has the advantages of accounting for the dependency of the drive and turn movements. Simpler models assume constant turning velocities and approximate robot movements to straight lines.

After defined, EKF requires the linearization of the model through the Taylor expansion. This includes computing the Jacobian of f with respect to X_k (Gx_k 3.3) and to u_{k+1} (Gu_{k+1} 3.4).

$$Gx_k = \frac{\partial f}{\partial X_k} = \begin{bmatrix} 1 & 0 & -\Delta x_{Odom} sin(\theta_k + \frac{\Delta\theta_{Odom}}{2}) - \Delta y_{Odom} cos(\theta_k + \frac{\Delta\theta_{Odom}}{2}) \\ 0 & 1 & \Delta x_{Odom} cos(\theta_k + \frac{\Delta\theta_{Odom}}{2}) - \Delta y_{Odom} sin(\theta_k + \frac{\Delta\theta_{Odom}}{2}) \\ 0 & 0 & 1 \end{bmatrix} \tag{3.3}$$

$$Gu_{k+1} = \frac{\partial f}{\partial u_k} = \begin{bmatrix} cos(\theta_k + \frac{\Delta\theta_{Odom}}{2}) & -sin(\theta_k + \frac{\Delta\theta_{Odom}}{2}) & -\frac{1}{2}\Delta x_{Odom} sin(\theta_k + \frac{\Delta\theta_{Odom}}{2}) - \frac{1}{2}\Delta y_{Odom} cos(\theta_k + \frac{\Delta\theta_{Odom}}{2}) \\ sin(\theta_k + \frac{\Delta\theta_{Odom}}{2}) & cos(\theta_k + \frac{\Delta\theta_{Odom}}{2}) & \frac{1}{2}\Delta x_{Odom} cos(\theta_k + \frac{\Delta\theta_{Odom}}{2}) - \frac{1}{2}\Delta y_{Odom} sin(\theta_k + \frac{\Delta\theta_{Odom}}{2}) \\ 0 & 0 & 1 \end{bmatrix} \tag{3.4}$$

Finally, to represent the uncertainty associated with the odometry readings, the state model also adds a random normal distributed variable $N(0,Q)$. Each direction of movement is assumed independent.

$$Q = \begin{bmatrix} \sigma^2_{\Delta x_{Odom}} & 0 & 0 \\ 0 & \sigma^2_{\Delta y_{Odom}} & 0 \\ 0 & 0 & \sigma^2_{\Delta\theta_{Odom}} \end{bmatrix} \tag{3.5}$$

Concluding, the chosen state transition model intrinsically states that the variation of the odometry readings is a good approximation of the variation of the true pose and that this approximation is modeled by a gaussian distribution.

3.3.1.2 Observation Model

Similarly, EKF's correction phase will also require a model to deal with the inputted measurements, also referred as Observation Model (3.6). It defines the range to beacon i as the actual Euclidean distance h between the position and the known beacon localization. The expected value of the measurement given the pose estimate is given by $h(\widehat{X_k}, M_{Bi})$. The range bearings were not given directly and thus not taken into account in the model, although they could theoretically be calculated by the combination of measurements from more than one beacon. Once again the process is affected by an additive Gaussian noise with zero mean and covariance R, a parameter to be tunned accordingly to the sensor error characteristics.

$$Z_{Bi} = r_{Bi} = hX_k, M_{Bi} + N(0,R) \qquad R = \begin{bmatrix} \sigma_r^2 \end{bmatrix} \tag{3.6}$$

$$h(\widehat{X}_k, M_{Bi}) = \sqrt{(x_{Bi} - \widehat{x}_k)^2 + (y_{Bi} - \widehat{y}_k)^2} \tag{3.7}$$

As well as for the state transition model, the Jacobian of h related to X_k (Hz_{ki} 3.8) will be computed for the purposes of the system linearization. Não coloques "chapeu" em Z pois é uma medida.

$$Hz_{ki} = \begin{bmatrix} -\frac{x_{Bi}-\widehat{x}_k}{\sqrt{(x_{Bi}-\widehat{x}_k)^2+(y_{Bi}-\widehat{y}_k)^2)}} & -\frac{y_{Bi}-\widehat{y}_k}{\sqrt{(x_{Bi}-\widehat{x}_k)^2+(y_{Bi}-\widehat{y}_k)^2)}} & 0 \end{bmatrix} \tag{3.8}$$

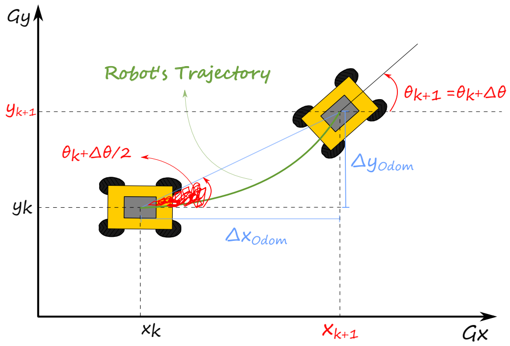


Figure 3.2: Odometry State Transition Model

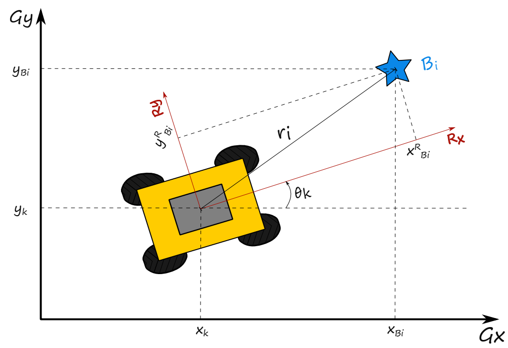


Figure 3.3: Range Observation Model

3.3.1.3 Implementation

After preliminary considerations, the algorithm can now be described. Our implementation (Algorithm 1) was based on the EKF Localization with known correspondences proposed by Thrun in [1].

The algorithm starts with the prediction step, where the state transition model is applied and linearized (lines 1:3). The prediction of the new state covariance P_k is also computed given the previous state uncertainty P_{k-1} and the propagation of the state and motion data around the current state (line 4). In fact, this simply means that the certainty of the new state is based on propagations of the previous state and the odometry values weighted by their own certainties.

Without any state correction from the sensor, the filter will accumulate noise and P_k will gradually increase. However, in the presence of new observations, the uncertainty is reduced deflating P_k. When new beacon data arrives, the algorithm cycles through each detected measurement and computes the expected observations at line 6.

If an outlier is not detected then the state is updated relatively to the Kalman Gain K_i (line 10:12). K_i measures the uncertainty of the sensor measurements relatively to the predicted state.

Finally, after updating the state and respective covariance for each beacon range, the algorithm terminates.

Algorithm 1 EKF Localization Algorithm with Known Measurement correspondences

Input: $X_{k-1}, u_k, P_{k-1}, R, Q, ZB_k^T$
Output: X_k, P_k

PREDICTION

$\widehat{X_k} = f(X_{k-1}, u_k)$
$Gx_k = \frac{\partial f}{\partial X}$
$Gu_k = \frac{\partial f}{\partial u}$
$P_k = Gx_k P_{k-1} Gx_k^T + Gu_k Q Gu_k^T$

CORRECTION

for $i \leftarrow 1$ to N_B **do**
    $\widehat{Z_{ki}} = h(\widehat{X_k}, M_{Bi})$
    $Hz_{ki} = \frac{\partial h}{\partial X}$
    $S_{ki} = [Hz_{ki} \widehat{P_k} Hz_{ki}^T + R]$
    if ! $Outlier\_Detected$ **then**
        $K_i = \widehat{P_k} Hz_{ki}^T S_{ki}^{-1}$
        $\widehat{X_k} = \widehat{X_k} + K_i[Z_{ki} - \widehat{Z_{ki}}]$
        $\widehat{P_k} = [I - K_i Hz_{ki}]\widehat{P_k}$
    end if
end for

$X_k = \widehat{X_k}$
$P_k = \widehat{P_k}$

3.3.1.4 Outliers Detection

Generally, the measurements in a robotic system like this are prone to unmodeled errors due to hardware faults, unexpected changes in the environment or even faulty beacon detections. For a proper use of the observations, the process needs to be able to detect and cope with these unreliable data whose characteristics deviate from the normal pattern. This phase is called Outlier Detection. There are several ways to approach the problem. In presence of a multivariate data, one of the common methods is using the Mahalanobis' distance (MD) (3.9) as a statistical measure of the probability of some observation belonging to a certain dataset. This method has been used successfully in different applications in [104] [105] and consists of computing the normalized distance between one point and all the population.The Euclidean Distance could be used but MD takes into account not only the distance to the mean but also the direction (i.e covariance). As a matter of fact, MD is equal to the Euclidean distance only when the covariance matrix is the identity (all the variables are independent and with the same variance). This statistical approach for outlier rejections is illustrated in Figure 3.4.

$$Md(v) = \sqrt{(v-\mu)^T S^{-1} (v-\mu)} \tag{3.9}$$

Algorithm 2 applies the concept to the EKF localization. Since only one sensor measurement

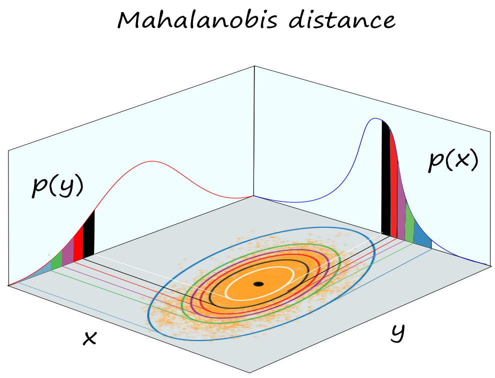


Figure 3.4: Mahalanobis' distance with different thresholds applied to a multivariate distribution. Outliers are removed if they are outside of a specific ellipse that represents a certain probability in the distribution. The different ellipses represent different MD's and hence different probability thresholds.

is analyzed at a time, we assume that the current estimated range $\widehat{Z_k}$ is the mean and S represents a combination of the uncertainty of the state and the actual sensor measurement (line 8 in algorithm 1).

Algorithm 2 Outlier Detection for EKF

Input: $S_{ki}, \widehat{Z_{ki}}, Z_{ki}$
Output: $isOutlier$
1: $Md(Z_{ki}) = \sqrt{(Z_{ki} - \widehat{Z_{ki}})^T S_{ki}^{-1} (Z_{ki} - \widehat{Z_{ki}})}$
2: **if** $Md(Z_{ki}) > threshold$ **then**
3:     **return** true
4: **else**
5:     **return** false
6: **end if**

Choosing the threshold (line 2) can be done by simply analyzing the data or by determining some probabilistic statistical parameter. Here it was set accordingly to the χ^2 probability table so that the observations with less than 5% of probability were cut out.

3.3.1.5 Tunning and Practical Considerations

In practice, a suitable EKF requires prior tuning of some parameters: the initial state error covariance P_0 and the noise covariances associated with the process Q and the measurements R. This is perhaps one of the most crucial steps of the EKF design since improper specifications can yield poor filter performance or even localization divergence.

Choosing P_0 is essentially related to the confidence that the algorithm has in the provided initial state X_0, so it will only affect the filter to a certain rate. After the initialization, the matrix P

is constantly updated and unless the system suffers unexpected major perturbations, it will start to converge to a steady state.

On the other hand, Q and R have a greater impact in the filter's performance and evolution. Depending on the implementation they can be constant or time-variant. Either way, their choice is representative of how valuable are the respective processes to the estimation.

Most authors consider Q the most critical and hardest design choice since R can be determined by the sensor's data characteristics [106]. In general, a small Q provides smoother results but can lead to divergences if odometry data considerably deviates from the expected model. It also shouldn't be too large to avoid large fluctuations in the state and large final uncertainty.

Even more important than each individual choice seems to be the ratio between P and R that will set the Kalman Gain. In general, small gains ($R \gg P$) lead to slow convergence and slow responses to system changes whereas larger gains may result in unstable estimation due to a bigger influence of more recent measurements [107]. Figure 3.5 captures the impact of the P/R ratio in the filter propagation error. Hence, it can be concluded that tunning an EKF is essentially finding a good trade-off between convergence rate and stability.

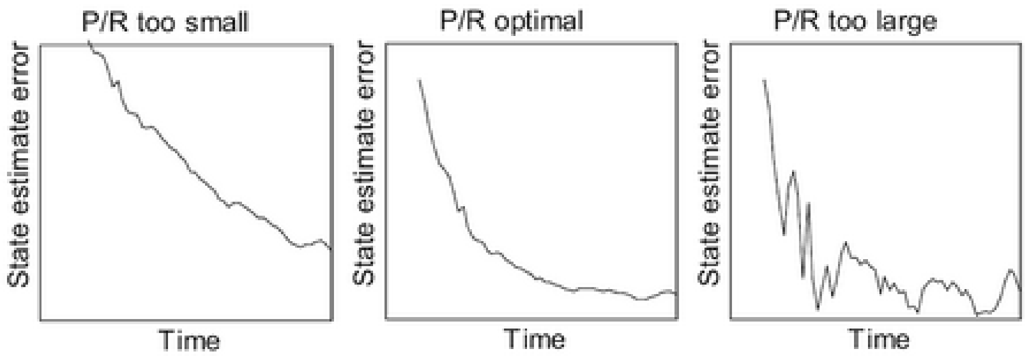


Figure 3.5: Effect of P/R ratio in a Kalman Filter propagation error. Reprinted from [107]

Several algorithms have been developed to properly tune an EKF but for the most cases a manual approach based on trial-error is simpler and enough. Given that the filter's model is only an approximation of the real one, Groves suggests, as a rule of thumb, to use parameters that can give a state uncertainty of around 2 or 3 times larger than the actual expected standard deviation in order to keep the estimation stable.

Lastly, it should also be noted that EKF performance is affected by different factors like changes of environment conditions, even for the same system and parameters. For this reason, the filter shouldn't be tuned to optimally fit a particular calibration data.

Chapter 4

Experimental Methodology

This chapter describes the methodology of experiments of the chosen approaches. The first chapter gives an overview of the implementation platforms, namely AgRob V16, the robot, and Pozyx, the localization beacon system. The second section outlines the tests performed and characterizes the respective environments.

4.1 Research Platforms Description

4.1.1 AgRob V16

AgRob V.16 (Figure 4.2) is a research agricultural robot developed by The Center of Industrial Robotics and Intelligent System of INESC TEC [1] with the purpose of carrying out different tasks in a vineyard environment.

AgRob V.16 is a continuation of previous works on AgRob V.14 (Figure 4.1), the preceding version. Because it is bigger and heavier (50Kg against V14's 15Kg), AgRob V.16 is more robust and can now support several types of mechanical components for execution of complex agricultural tasks.

Figure 4.1: AgRob V.14

Figure 4.2: AgRob V.16

[1] http://criis.inesctec.pt

It is built on top of a low center of gravity platform that along with its four-wheel mechanical traction allows an autonomous navigation in harsh terrains with a maximum speed of 1.0 m/s. The sensing system is composed of different hardware: RTK-GPS, LIDAR, IMU, stereo cameras and RGB-D cameras. All of these are managed and integrated by one Intel NUC i7 and two Raspberry Pi 3 running Ubuntu 12.04 along with the Robotic Operating System (ROS).

Currently, the several sensors mentioned are used for localizing the robot and can yield a mapping accuracy of around 20/30 cm. Adding a beacon based localization technology aims to increase the redundancy and hence the accuracy of the current localization that may be needed for more specific tasks and for a secure navigation.

More details on the AgRob project and respective specifications can be found in [108] and [2].

4.1.2 Pozyx System

For the UWB ranging framework implementation, we selected Pozyx [109], a commercial solution for accurate ranging, positioning and motion sensing. It consists of 5 modules with an embedded *DecaWave* [43] chip - one tag working with an Arduino UNO and 4 beacons - which together can provide raw range measurements, position estimations (2D or 3D) and orientation. The latter is achieved by fusing an accelerometer, a gyroscope, a magnetometer and a pressure sensor. The basic architecture of a Pozyx tag is depicted in Figure 4.3.

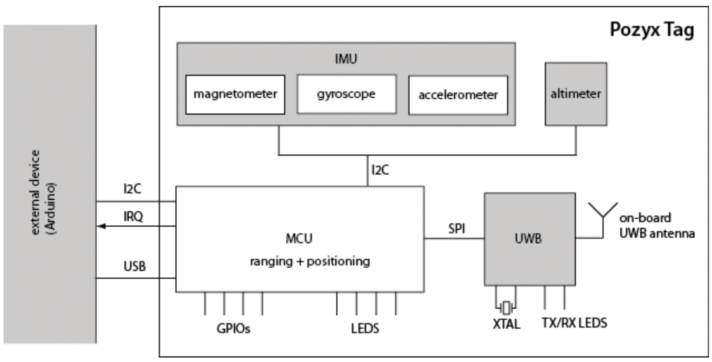
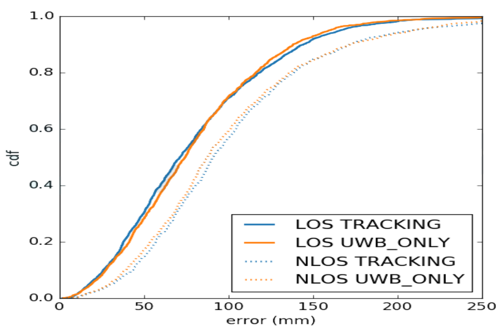


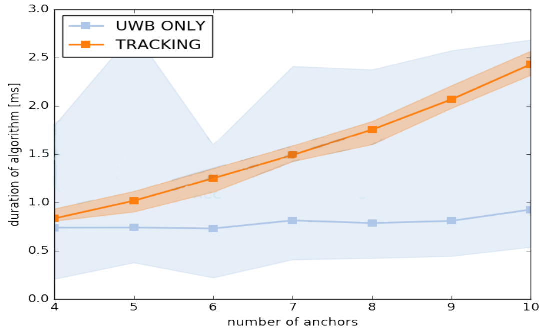
Figure 4.3: Architecture of a Pozyx Tag. Retrieved from [109]

As far as the ranging procedure is concern, it is based on the two-way TOF technique, although the system can also output the RSS of the signals received by the tag. Its expected accuracy in Line-of-Sight conditions is around 10 cm.

One of the work approaches was comparing our EKF Localization with the Pozyx algorithms. The positioning feature supports 2D, 2.5D and 3D dimensions and is provided through one of two different algorithms: ***UWB-only algorithm***, that estimates the position only by the Trilateration of UWB measurements. It is specially optimized to deal with Non-Line-Of-Sight cases; ***Tracking algorithm***, that also fuses IMU data and previous steps information. It is designed to work with 3D dimension and unlike *UWB-only*, requires update rates > 1 Hz. Figure 4.4a shows that both algorithms performed similarly in an indoor environment, with reported average accuracies of 92



(a) Cumulative distribution function of the positioning errors in a (x-y) plane.



(b) Experimental measured algorithm delays as a function of the number of beacons. The solid lines show the average time, whereas the shaded areas indicate the spread.

Figure 4.4: Experimental Tests under NLOS and LOS situations in a indoor environment. Adapted from [109].

mm and 140 mm respectively for LOS and NLOS situation. Figure 4.4b exposes the performance of the algorithms relatively to the duration. Given its more simple implementation, UWB-only algorithm is faster and always approximately the same, whereas the Tracking algorithm highly depends on the number of beacons used. On the other hand, the spread (minimum and maximum times measured) is much higher for UWB.

4.1.3 UWB configuration

The UWB communication between the modules can have different configurations that may impact the system performance, not only in terms of accuracy but also of energy consumption and update rates. These settings can be set according to four different parameters:

- **Channel**: The communication between devices has 6 independent UWB channels (Table 4.1). Generally, lower channel numbers have lower frequencies which increase the communication range.
- **Bitrate**: velocity of data transmission. The choice is either 110kbit/sec, 850kbit/sec or 6.81Mbit/sec. A higher value will result in shorter messages and consequently faster communication. It can, however, reduce receiver sensitivity and the maximum range achievable.
- **Pulse Repetition Frequency (PRF)**: rate of signal pulse repetition. It is set to either 16MHz or 64MHz. Choosing the first may reduce the power consumption, but the difference is not too significantly.
- **Preamble Length**: number of symbols sent in the UWB packet's preamble. This setting has 8 different options: 4096, 2048, 1536, 1024, 512 , 256 , 128 , or 64 symbol. Longer lengths will commonly increase the radio range at the cost of longer transmission and receiving times.

Table 4.1: Pozyx's UWB Channel Characteristics

Channel	Center Frequency (MHz)	Bandwidth (MHz)
1	3494.4	499.2
2	3993.6	499.2
3	4492.8	499.2
4	3993.6	1331.2
5	6489.6	499.2
7	6489.6	1331.2

For the implementations tests, firmware v0.9 [2], that provides maximum data rates of 150Hz for orientation, 60Hz for ranging and 15Hz for positioning, was used.

4.2 Experimental Tests

To fully characterize the system and evaluate our approaches some experiments were conducted. The tests had the objective of analyzing three main aspects of the implementation:

- UWB Range Error characterization
- Pozyx positioning characterization tests
- Fusion of odometry and Pozyx ranges through EKF

To integrate Pozyx, some examples of the *Pozyx Arduino Library* [110] were adapted: *Ready_to_Range* (for Range-Only implementation) and *Ready_to_Localize* (for direct Positioning implementation). For the communication between the sensor and the Robot, a ROS node was created. The data transmission from Arduino to ROS was done by serial port using the *Termios* library [3] which after validation, published the information received with a rate of 10Hz in a native ROS Pose [4] message and in a message created for publishing an array of Pozyx ranges.

Finally, to analyze the results, test and tune the EKF, some MATLAB scripts were implemented. Since the main scope of the thesis was to study the accuracy of this implementation, post-processing in MATLAB is acceptable. In future work for a proper integration, the EKF should be converted to a ROS node.

4.2.1 Test Environment

For convenience and to get an accurate ground-truth, the majority of the tests took place in an outdoor environment at the Faculty of Engineering, University of Porto, Portugal (Figure 4.5).

[2] Recently, the firmware was updated but all the tests performed were still done under v0.9

[3] Library to deal I/O interfaces http://pubs.opengroup.org/onlinepubs/7908799/xsh/termios.h.html

[4] ROS PoseStamped message: http://docs.ros.org/api/geometry_msgs/html/msg/PoseStamped.html

Although not being particularly similar to an actual vineyard, those were environments with some vegetation and with no reliable GPS signal (because of the dense building structure).

Unless said otherwise the basic UWB configuration for the tests was: **Channel** 2 (Center frequency 3993.6MHz and bandwidth 499.2 MHz), for which the antenna is supposed to have better performance according to the manufacturers; **Bitrate** 110kBit/s - we were interested in having the best range performance and the rate of transmission was not so important; **PRF**: 64MHz -the default setting was used because its value is not said to influence the performance drastically; **Preamble length**: 1024 symbols - the default was also chosen in order to have a mid-term value.

All the Pozyx positioning data was extracted via the UWB-only algorithm in 2D.

Figure 4.5: Outdoor Environment for Localization and Pozyx Error Range Tests

4.2.2 Pozyx Error Characterization

To get a full characterization of the Pozyx system and its error, several tests were conducted. A first preliminary experiment was made indoors to analyze both the ranges and the positioning algorithm in a small Line-of-Sight scenario (**Indoor Test**). In order to test bigger ranges and environments closer to the real one, the rest of the experiments were made outdoors (**Positioning Outdoor Test** and **Range Outdoor Test**).

The **Indoor Test** setup consisted of an approximate rectangle of 6m x 4m with the 4 beacons positioned at the corners and the sensor placed in different positions (Figure 4.6). Both ranges and positions were extracted.

The Pozyx positioning algorithm was the focus on the **Positioning Outdoor Test**, this time outdoors and with bigger square sizes (Figure 4.7). Here two different antenna channels (2 and 7) were used in order to analyze the effect of some of the UWB parameters.

Finally, **Range Outdoor Test's** goal was to measure ranges at different distances and see how that impacted the error. As for the setup, progressively measurements to one beacon were done 1 m at a time until 10 m, 5 m at a time until 30 m and finally 10 m of interval until 60 m (1-10, 15, 20, 25, 30, 40, 50, 60 meters). The ground-truth data were obtained with a 30 m rigid measuring tape (Figure 4.8a).

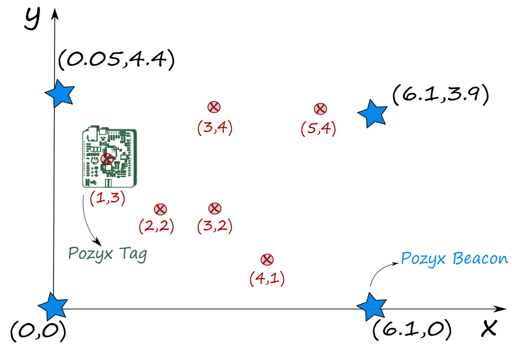


Figure 4.6: Indoor test setup. The Pozyx Tag was positioned at different positions marked as red crosses in the image and both ranges and positions were extracted

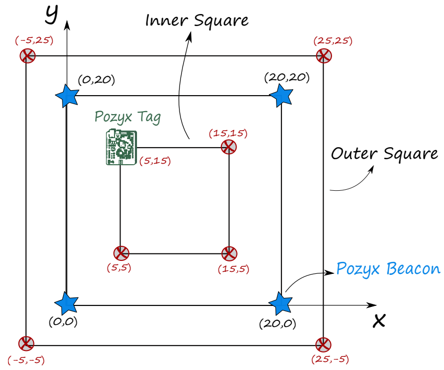
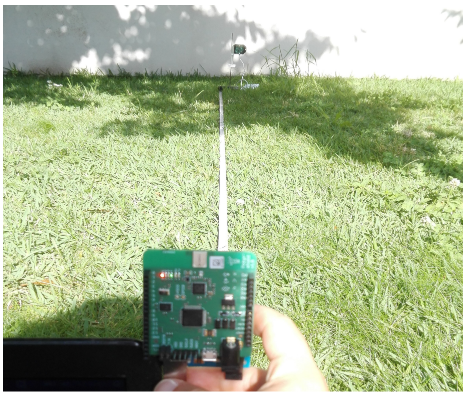
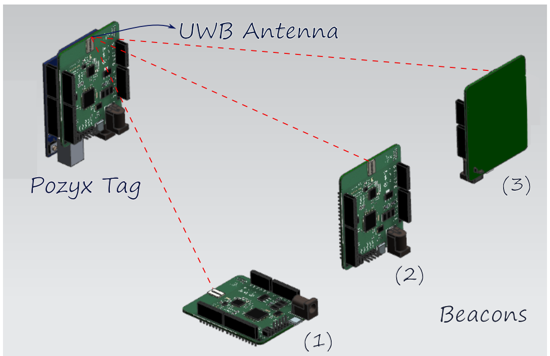


Figure 4.7: Outdoor Positioning test setup. The Pozyx beacons were the corners of a 20 m x 20 m square. Different positions were extracted in an outer square (30m x 30m) as well as in an inner square (10 m x 10 m)

Given the typical propagation sensitivity to antenna orientation, 3 different Pozyx orientations were tested: Vertical Front (with the antenna on top), Vertical Back and Horizontal 4.8b. Both the sensor and the beacon were about 20 cm from the floor.



(a) Range Test to one single beacon.



(b) Different Beacon Orientation: Horizontal (1); Vertical Back (2); Vertical Front (3)

Figure 4.8: Pozyx Range Test setup

4.2.3 Localization Tests

After the Pozyx characterization experiments, more real practical cases were tested. The 4 Pozyx beacons were spread in the corners of a 20 m x 20 m square, partially represented in Figure 4.9. The robot follow different trajectories so the impact of the beacons placement could also be explored. As a ground truth, a Laser Scan SLAM [5] was used since the GPS data acquired was nor reliable nor precise.

[5] computed by the Hector Slam ROS package `http://wiki.ros.org/hector_slam`

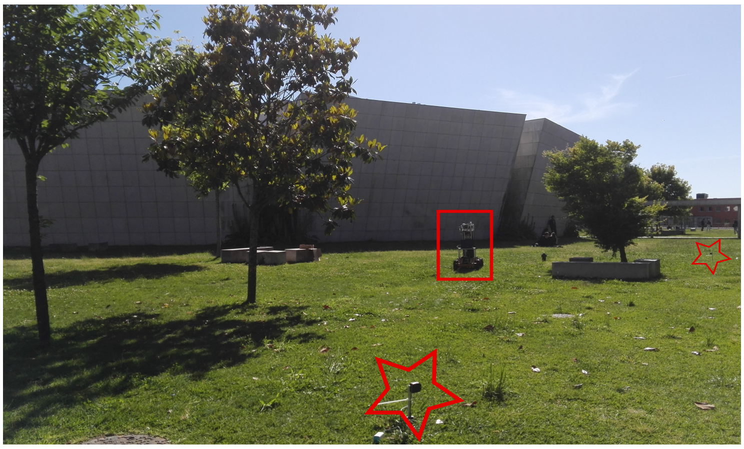


Figure 4.9: Outdoor Test of Pozyx Positioning and EKF Localization. The stars show the beacons placement referent to the robot (rectangle).

4.2.4 Localization in a real vineyard scenario

The localization and error tests were followed by an experiment in a real vineyard scenario owned by *Sogrape* [6] and situated at *Quinta do Seixo*, Valença do Douro, Portugal (Figure 4.10). Taking advantage of the vineyard structured environment, the beacons were placed on top of the trellis 4.11 and formed approximately a rectangular shape (40 m x 15 m) surrounding one vineyard row. The robot navigated back and forward inside this rectangle measuring the ranges to the beacons at around 10Hz. Since only 4 beacons were used, navigation in more than one row wasn't tested for now.

Figure 4.10: AgRob Localization Tests in Quinta do Seixo

Figure 4.11: Beacon placement in a vineyard trellis

[6] https://www.sograpevinhos.com/

Beacons Placement

Pozyx positioning algorithms need as an input the beacon localization. Although it can be done automatically, it is generally more accurate to do it manually. Extracting the best measurements possible in a beacon-based localization usually implies following some rules of thumb regarding the beacons placement in the world:

- Place beacons high and in the line-of-sight of the user in order to reduce obstructions;
- Place beacons vertically with the antenna on top to improve the signal reception;
- Spread beacons evenly around the user trying to cover different directions. If they are for example on a straight line, this will amplify errors and create unnecessary ambiguities.

Chapter 5

Results and Discussion

The implemented approaches performance is evaluated thoroughly in this chapter. The results for the different tests are described, starting with the indoor and outdoor Pozyx Error Characterization. Subsequently, the Localization implementations are validated and compared, authenticating the previous error characterization and giving some notes on the EKF tunning. Finally, the EKF Localization performance is also analyzed for the Vineyard environment along with some considerations about its application in different conditions.

For a more detailed description of the tests setup and environments we referred to section 4.2 in the previous chapter.

5.1 Pozyx Error Characterization

When characterizing the performance of a system it is important to be aware that an error can have different sources and be of different types. We'll focus on both accuracy and precision analysis, which are usually linked to systematic and random errors respectively. Although both are important, in this specific case, characterizing the precision of the sensor is of particular importance since it will be used to tune the EKF. Apart from that, accuracy measures how close are the observations to the real values, therefore the chosen ground-truth will affect the outcomes. Hence, more than the actual accuracy values we'll be looking for patterns in the standard deviations.

5.1.1 Indoor Test

As more detailed explained in section 4.2.2, for the indoor test, the beacons were spread in the corners of an approximate rectangle [(0,0) (6.1,0) (6.1,3.9) and (0.05,4.4)] and the tag was placed in 6 different positions inside it [(1,3) (2,2) (3,2) (3,4) (4,1) (5,4)]. Figure 5.2 plots the positions extracted by the Pozyx UWB-only algorithm along with each correspondent 95 % confidence ellipse (Figure 5.2). As it can be seen, except for points (3,2) and (4,1), a cluster of outliers was observed in specific places which inflated the covariance ellipse. This ellipse, whose center represents the data mean value and whose semi axis represent the covariance, also reveals that in general, y uncertainty is significantly bigger than x (the ellipse is stretched in the y direction).

In fact, Pozyx's antenna cannot perform equally in every direction (like every practical antenna). It radiates omnidirectionally in the x-z plane but not on the y-z plane (Figure 5.1). Therefore, different orientations between tag and beacons will cause variations in the performance (as also noted later in section5.1.3).

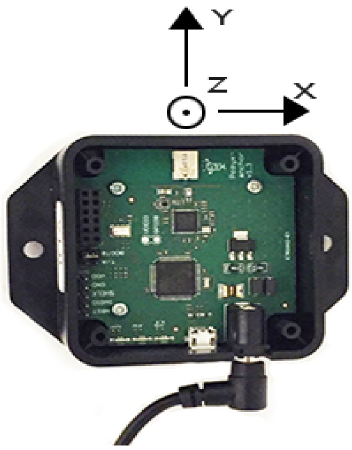


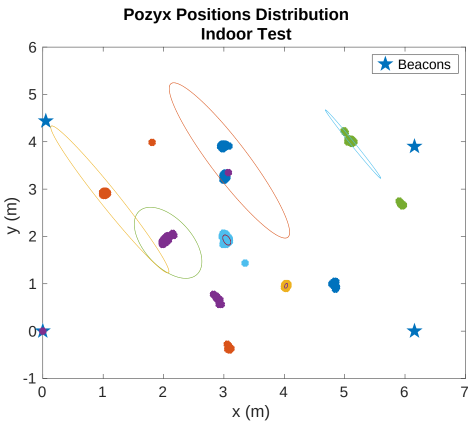
Figure 5.1: Pozyx Tag reference frame. The UWB antenna is the white chip on top. Retrive from [111]

The outlier detection proposed in chapter 3 was applied using a Mahalanobis distance (MD) of $\sqrt{5.99}$ (Figure 5.2b). Assuming that MD follows a chi-square distribution with 2 degrees of freedom, setting the threshold to this value implies that observations out of the 95% confidence area were cut off. By analyzing the resulting plot a small set of points for position (3,4) can still be identified. Since the two clusters of points are not only close but with almost the same x value, it is difficult to get rid of them, which was accomplished by decreasing the threshold for around $\sqrt{2.77}$, equivalent to $\chi^2_{0.25}$. One possible interpretation for the raw results could be that the best results are achieved by having the beacons evenly spread around the node. The positions for which the sensor is close to the center of the rectangle showed better estimations and with fewer outliers than the ones closer to the corners/beacons.

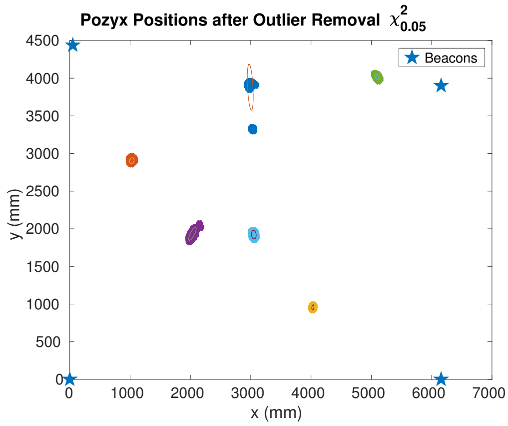
In what the ranges are concern, no correlation was found between the measurements and the outliers in the Pozyx UWB-only algorithm. They were quite constant overtime, fact reflected in the small and non-varying standard deviation (Figure 5.3a). Looking at the histogram shape 5.3b, we can also conclude that the error follows an approximately gaussian distribution enforcing the use of the EKF's gaussian process.

Furthermore, given that the covered area was small, no particular conclusions can be made about the correlation between the error and the distance. At a first sight, in the range of 10 meters, the error metrics appear to be constant over distances (Figure 5.3a).

In sum, the indoor test showed promising results for Pozyx. The resulting range accuracy had a mean absolute error of around 9.4 cm and an average standard deviation of 2 cm, which are very good results when comparing to another state of art technologies. Additionally, although the



(a) Raw Measurements



(b) Results after Outlier Removal

Figure 5.2: Pozyx UWB-only algorithm estimated positions with respective 95% confidence ellipses.

Pozyx outputted some unwanted outliers, they were well structured in clusters which permits a faster and easier removal procedure.

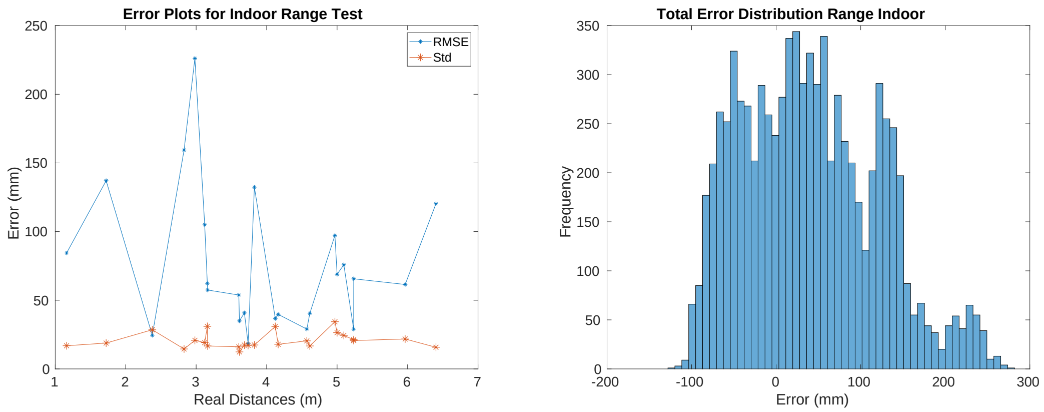
5.1.2 Positioning Outdoor Test

In the outdoor test, differences of using two different UWB communication channels and a wider working area were investigated. A total of 8 positions were extracted spread distinctively along the corners of two squares (an inner square of 10 m side and an outer square of 30 m side). A briefly quantitative analysis was performed and exposed in Table 5.1, where we can see that the two channels performed similarly except from the positions in the outer square with channel 7. From Figure 5.4a we can deduce that the considerably large RMSE is due to the right top corner of the outer square which presents two clusters of points and a large uncertainty ellipse. After the statistical Mahalonobis Outlier detection (with $\chi^2_{0.05}$) the correct points were wrongly removed causing the large error (Figure 5.4b)

Considering the differences between the inner and the outer square, the poor Geometric Dilution of Precision (GDOP, often applied to GPS localization algorithms) affecting the error is more evident in the latter. As explained in chapter 4, the beacons should be spread around the user in

Table 5.1: Pozyx UWB-only algorithm performance in two different channels. All the metrics were computed after the outlier detection phase

Channel	Inner Square				Outer Square			
	Std_X (mm)	Std_Y (mm)	Error (RMSE) (mm)	Outliers (%)	Std(X) (mm)	Std(Y) (mm)	Error (RMSE) (mm)	Outliers (%)
2	61	66	243	3	37	51	1019	9
7	60	62	206	5	535	124	5453	14



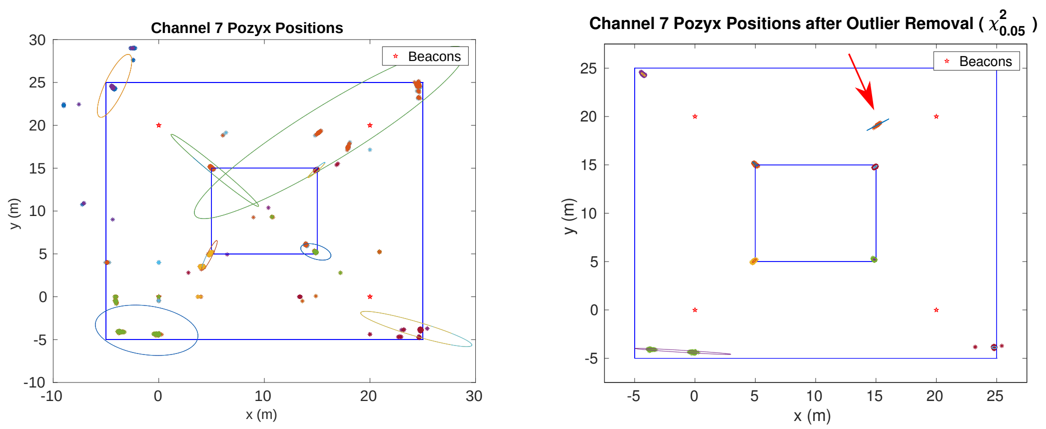
(a) Indoor Error Metrics Results: Root Mean Square Error (RMSE) and Standard Deviation (Std)

(b) Error Distribution Histogram

Figure 5.3: Pozyx Range Error Characterization Results

order to cover different directions, otherwise small changes in the measurements will largely affect the intersection of the trilateration circles and consequently amplify the error.

Results for channel 7 are also illustrated in Figure 5.4. Overall, as in the indoor test, the algorithm reveals a jittery and unstable performance, but this time in a much larger scale, most probably due to the wider working area. By statistically removing outliers, the resulting localization becomes cleaner (Figure 5.4b) and the error metrics fairly acceptable, however, it is still uncertain on how reliable can be its localization as a stand-alone system. This is especially true for large areas with distances between sensor and beacons easily passing the 25/30 meters range.



(a) Pozyx UWB-only algorithm results for UWB channel 7 before outlier detection

(b) after outlier detection

Figure 5.4: Pozyx UWB-only algorithm results for UWB channel 7

5.1.3 Range Outdoor Test

The ranging test aimed an accuracy and precision analysis of the Pozyx ranges so they could be properly used in the localization algorithm. Data was collected from a Line of Sight ranging communication between one beacon and the tag at increasing positions (1, 2, 3 ... 10, 15, 20, 25, 30, 40, 50, 60 meters) To characterize the ranging dependency on the antenna orientation, Table 5.2 was computed with the Root Mean Square Error (RMSE), Standard Deviation (Std) and percentage of time out errors (those where no actual value was measured).

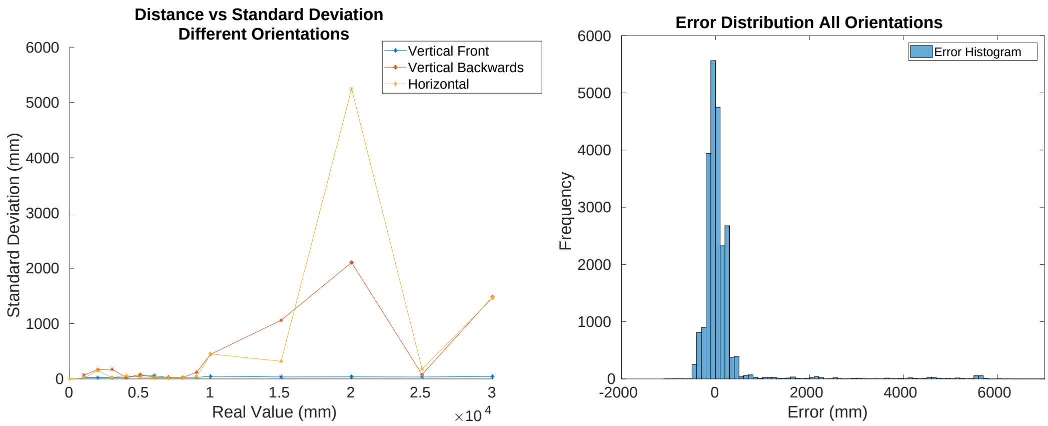
Table 5.2: Refers to the performance results for different antenna orientations. Under 10 meters the results don't follow any specific pattern and are always around the same values so only their average is presented.

Distance (m)	Vertical Front			Vertical Back			Horizontal Up		
	Error (RMSE) (mm)	Std (mm)	Timeouts (%)	Error (mm)	Std (mm)	Timeouts (%)	Error (mm)	Std (mm)	Timeouts (%)
<= 10	83	33	1	210	117	2	196	83	1
15	71	36	7	1059	1060	30	342	319	61
20	152	38	18	2371	2105	52	5319	5246	99
25	196	35	25	112	79	40	231	180	95
30	170	43	5	1626	1483	1	920	1464	71
40	4959	919	15	4905	732	39			
50	129	49	10	5516	792	6			
60	2666	1095	6						

Along with Figure 5.5, the table demonstrates that both the orientation and the distance between tag and beacon have a considerable impact on the measurements. As previously explained in the indoor test (section 5.1.1) the distinct performance between x-z and y-z planes propagation can have an impact on the obtained results, so it comes as no surprise that the performance is better for the vertical front position as opposed to a horizontal one where the timeout communication errors are higher and data received after 30/40 m is not very reliable. The table also suggests that although having the same orientation, when beacon and tag antennas are not facing each other, the propagation follows a different path impacting the resulting performance.

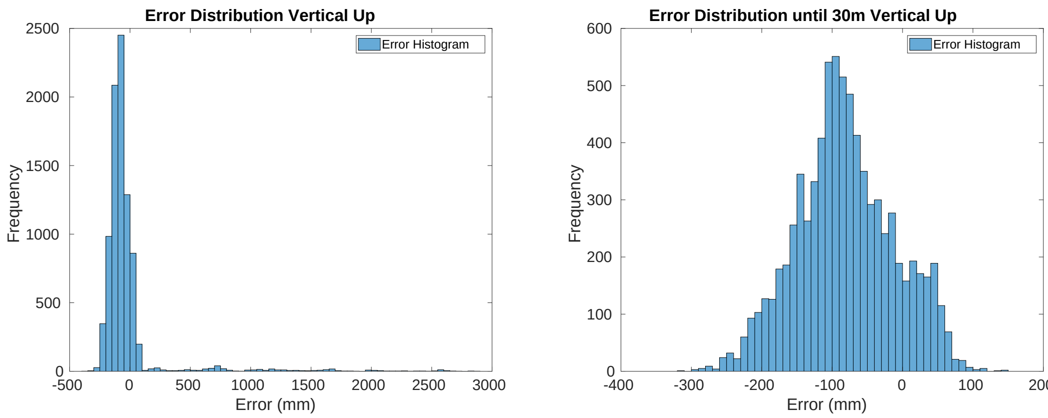
Given higher standard deviations, the error distribution when considering all the orientations presented some unexpected big values that fall from the normal gaussian shape (Figure 5.5b). Furthermore, the performance is also clearly degraded by increasing distance as measurements become more variable (Figure 5.5a). This is also true even for the best orientation (Vertical Front) as demonstrated by the comparison of histograms 5.6a and 5.6b. The first illustrates a perfect distribution error up until 30 m between tag and sensor. On the other hand, after 30 meters, the measurements start to be less reliable presenting some higher errors.

Throughout navigation, although both the embedded sensor and the beacons can be placed vertically, they will have different orientations towards each other. Thus, in future work, it will be interesting to do a more intensive study of these differences and to include a bearing measurement in the sensor observation model for the EKF. For now, we'll be focusing on the results for the vertical front orientation to define the error variables of the filter.



(a) Standard Deviations over distance (b) Pozyx Ranges error distribution

Figure 5.5: Pozyx Ranges Error for Different Orientations



(a) Total error distribution (b) Error distribution until 30 meters

Figure 5.6: Pozyx Ranges Error Distribution for Vertical Front orientation

Generally, if restricted to around 30 meters, the ranging procedure achieves a good accuracy with an RMSE between 4 to 20 cm and a standard deviation of around 2/6 mm (Figure 5.7), showing that, if carefully integrated the sensor can be highly valuable for the localization system.

Finally, since the sensor provides the received signal strength of every communication, we also tested the ability of processing outliers by this metric. Unfortunately, the UWB RSS didn't show any particular pattern relatively to the ranges that provided higher errors (Figure 5.8). Although, having a tendency of decaying with increasing distances and slightly different values for different orientations, more complex tests should be performed if in need of an accurate antenna propagation model.

5.2 Outdoor Localization Test

Passing on to the actual robot localization system, data processing and analysis was done with two main objectives. Firstly, the EKF tuning and then, the comparison our implementation with

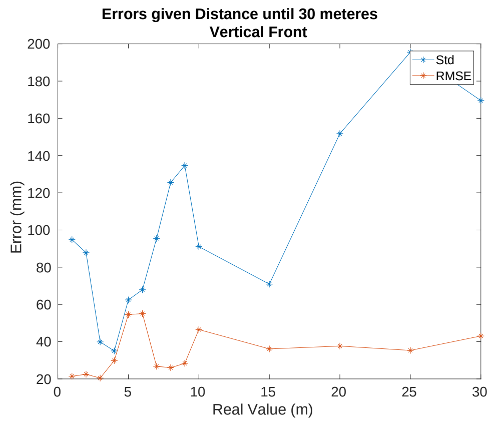


Figure 5.7: Standard Deviations over distance

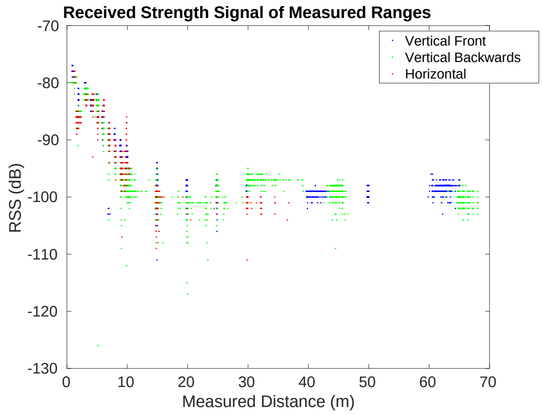


Figure 5.8: Received Signal Strength for different distances and orientations

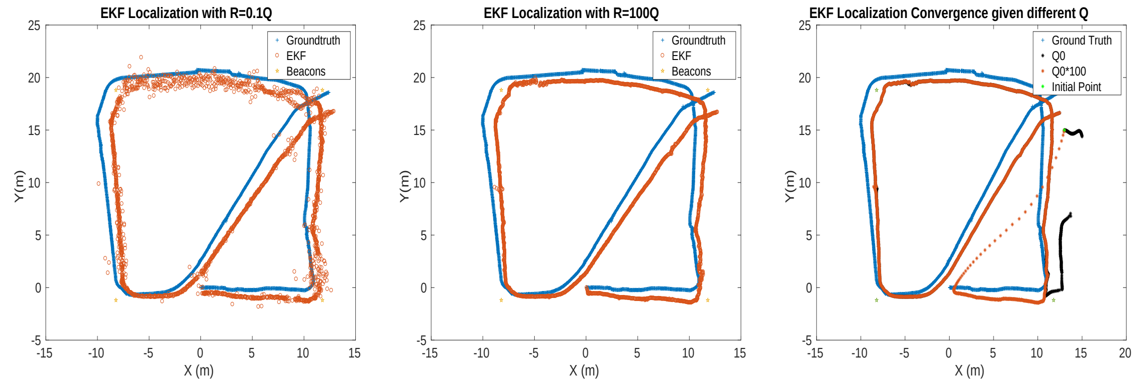
the Pozyx UWB-only algorithm and with other sources of localization, namely the raw Odometry readings and a Laser Scan using a precomputed map obtained by a SLAM method (considered as ground truth).

5.2.0.1 EKF Tuning

An important step in the post-processing step was the EKF tuning. Changing its parameters affects the convergence of the algorithm as well as the smoothness of the resulting trajectory estimation. Considering the previous noise characterization, R and Q were adjusted so that the estimation results presented weren't neither to noise sensitive neither too slow. The effect of different choices of Q and R is showed in figure 5.9, in which we can see a clearly smoother trajectory for R > Q. One of the reasons could be the faster update rate of odometry. Trusting too much on range measurements given that they don't come as often as the odometry ones, will induce jumps in the trajectory. On the other hand, for smaller Q's the algorithm will converge much slower to the real trajectory, as inspected in Figure 5.9c using a poor initial state estimation.

After some trial error tests on different datasets, Q was adjusted to $\begin{pmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 0.02 \end{pmatrix}$. R's value, by its turn, was set accordingly to the variance obtained in the Pozyx Range Characterization. From the difference observed on ranges until 30 meters, we decided to have a variable R accordingly to the measured distance. R is 0.3 if the range is smaller than 30 m and 0.9 otherwise. Regarding the initial state estimates, P_0 is a 3x3 identity matrix and x_0 can be fairly approximated by $X_0 Odom$.

Relatively to the outlier detection phase, the ranging measurements didn't result in many outliers, except for the timeout ones which are instantly observed and don't need further calculations to be detected (Figure 5.10). Therefore, the effect of including the Outlier Detection Filter is not a big improvement simply because there are not many outliers to get rid of. To further test the effectiveness of the filter more tests with wider areas should be done.



(a) EKF Estimation with higher confidence in ranges

(b) EKF Estimation with higher confidence in motion model

(c) EKF convergence with different tunning parameters given poor initial state estimation

Figure 5.9: EKF Localization Tunning

5.2.0.2 Pozyx Positioning vs Pozyx Range + EKF

The Pozyx Positioning and the EKF Localization are compared in Figure 5.11. Both the procedures yield reasonable results, especially when compared to the Odometry localization that is clearly affected by some wheel slippage in the curves (Figure 5.11a). However, as presented in Figure 5.11b, the native Pozyx Localization presents a lot more outliers than our EKF Localization.

Lastly, further evaluation was done by exploring different trajectories in which once again the EKF Localization outperforms the Pozyx UWB-only algorithm. The larger number of outliers for the Pozyx Positioning algorithm in Figure 5.12c also give some notes on the right positioning of the beacons relatively to the sensor. Since it only trilaterates UWB ranges, the output is more sensitive to the overall network "geometric arrangement" and the fact that it is only moving near two of the beacons seems to impact the resulting performance. Thus, one can conclude that the beacons should be spread out as evenly as possible around the robot's trajectory area so different directions can be covered. Contrarily to the Pozyx algorithm, the EKF Localization is not based on this method so it doesn't seem to be so affected by this issue.

5.3 Vineyard Localization Test

The first test in the real vineyard showed promising results regarding our EKF implementation but also highlighted some of the precautions that should be taken into account in the presence of more complex environments. For instance, because we were dealing with a wider and curvier area, ground truth measurements for both the trajectory and the beacons locations were difficult to obtain. The GPS signal in the vineyard is not particularly strong, neither is its accuracy and using other measuring instruments is tricky and not precise. Hence, we used the Pozyx ranges to "automatically" calibrate the beacons positions by trilateration. We further computed AgRob's

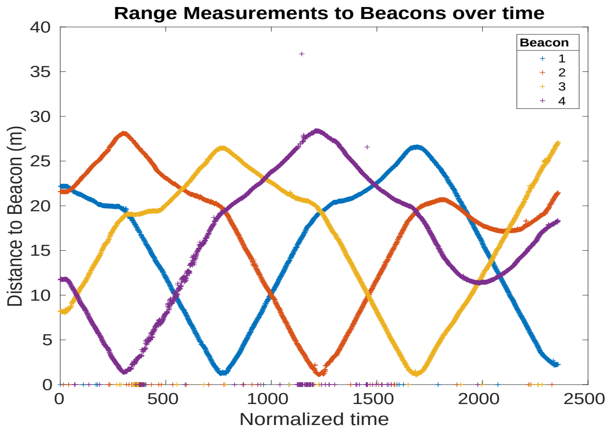
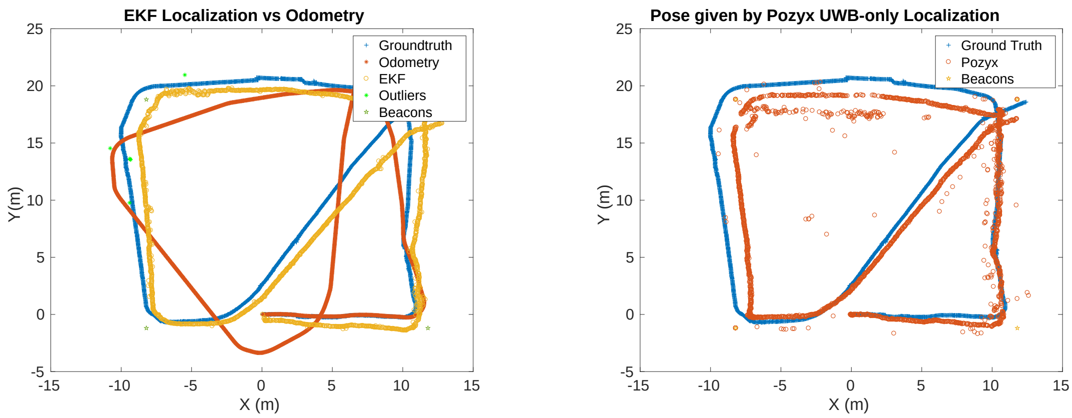


Figure 5.10: Ranging measurements over time in the Outdoor Localization Test



(a) EKF Localization and Odometry Readings

(b) Pozyx default Algorithm

Figure 5.11: EKF Localization and Pozyx UWB-only algorithm results comparison

laser data with *Hector Slam* as in the previous tests for reference ground truth. The calibration of the beacons was done in the post-processing phase and validated through comparison with Geolocation. Since it was all done a-posteriori, the Pozyx native algorithm (which needs the beacons mapping as input) wasn't tested and thus is not presented in this section. However, having tested the accuracy of the calibration by the beacons ranges, it would be interesting to also compare that in future Vineyard tests.

At a first sight, we analyze the impact of the denser environment in the ranging measurements. Figure 5.13 suggests a larger number of outliers due to timeout communication (plotted as 0) and a maximum range of 50 meters, although it may not be that reliable after 30 meters, confirming the Outdoor Ranging Test results. In light of the harder conditions with, for example, vegetation possibly blocking radio communication, the results achieved corroborate the UWB technology advantages in multipath environments and complex systems.

Additionally, the failures of odometry due to the harsh terrain are well demonstrated in Figure 5.14b. The robot navigates through one vineyard row and comes back to the initial point, but the

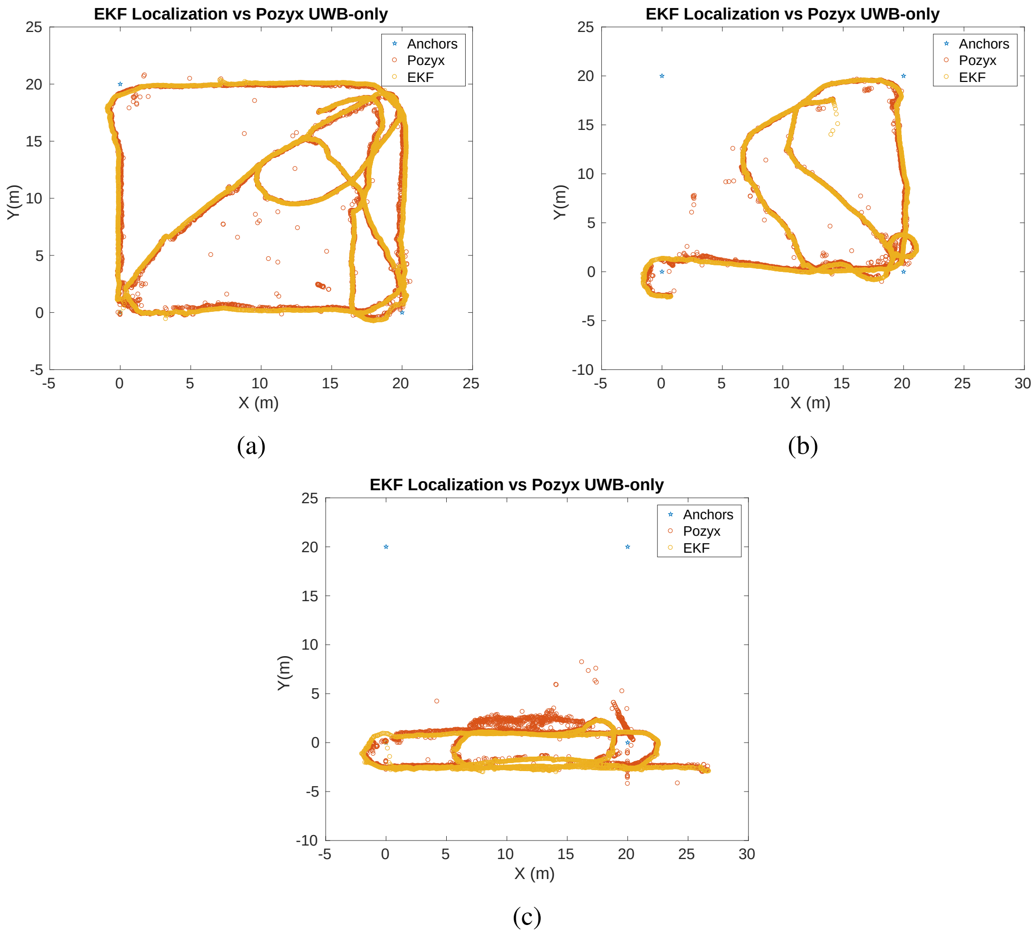


Figure 5.12: Pozyx Algorithm and EKF Localization on Different trajectories

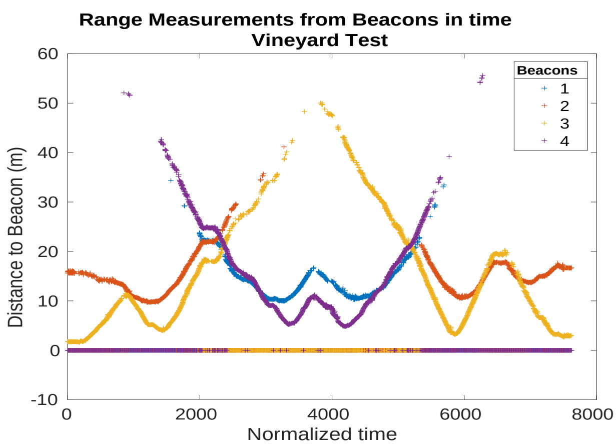
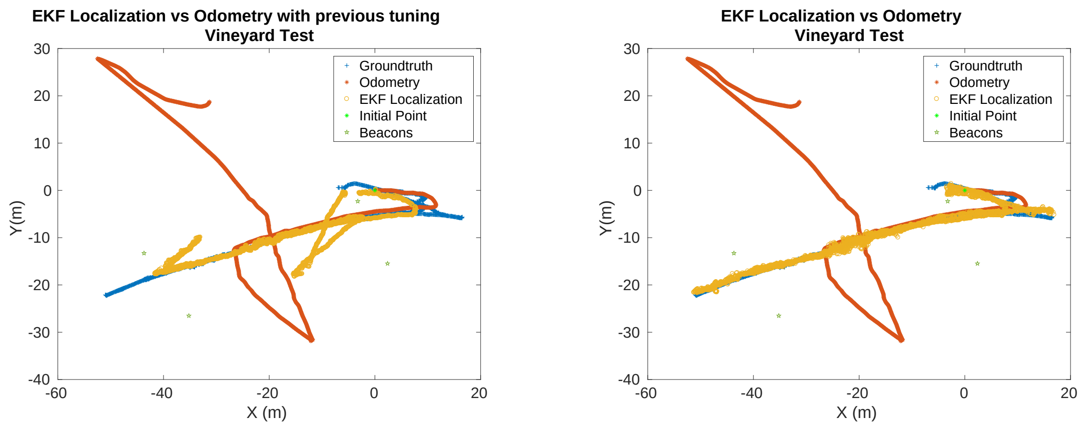


Figure 5.13: Ranging measurements over time in the Vineyard Localization Test



(a) EKF Localization Results with previous tunned parameters from section 5.2.0.1

(b) Newly tunned EKF Localization compared with Odometry

Figure 5.14: Localization Estimation in a Vineyard Environment

odometry localization completely goes off path at the middle of the trajectory. Because it is fused with the range observations, the impact of this divergence on the EKF algorithm is present but not critical.

Our implementation performs less smoother than the localization tests done in the previous tests, but it can still give a very fair approximation of the truth localization. Four beacons spread in a vineyard row showed to accurately localize the robot. On the other hand, ranges are limited to 40/50 meters, which even though is a very decent result considering the environmental conditions, may present some issues when navigating through different rows further away. From this reason, a bigger network of sensor beacons would be very interesting to test in the vineyard to increase the operating range.

Lastly, it should be noted that the EKF as tuned in section 5.2.0.1 did not perform as good (Figure 5.14a). Instead, different parameters were used, increasing the expected uncertainty of the odometry motion model ($Q = 100Q_{previousTest}$). This comes as a confirmation of one of the (expected) EKF disadvantages: the delicate process of tunning the filter and its variation in different environmental conditions. This was already expected given the vineyard's rocky and uneven terrain as opposed the first test one. Table 5.3 summarizes the impact of different EKF parameters on the resulting localization. More confidence in odometry measurements (Figure 5.14a) yields a smoother algorithm but diverges at some point whereas more confidence in ranging data (Figure 5.14b) leads to a less smoother result but the localization converges to the ground-truth.

Table 5.3: Impact of different EKF Tunning Parameters on Localization

Figure	EKF Parameters				Impact			
	Q_X	Q_Y	Q_θ	R	Odometry Confidence	Pozyx Confidence	Smoothness	Convergence
5.14a	0.01	0.01	0.01	0.3	+	-	+	*X*
5.14b	1	1	1	0.3	-	+	-	✓

Chapter 6

Conclusions and Future Work

During the work developed, a beacon-based localization was successfully implemented and evaluated in an agricultural robot.

The proposed EKF implementation presented better results than the UWB-only Pozyx Algorithm leading to smoother estimations of the robot's pose and proving its efficiency in robotics probabilistic estimation. On the other hand, after tests in different environments, the need for a careful tunning procedure was evident. This process revealed to be fairly easy in more stable environments like the one from the first localization test outdoors, but required more attention in the vineyard scenario. One of the reasons is the fact that the Odometry performed much poorer given a highly uneven terrain which affects the resulting estimation. Hence the need to give more confidence to the Pozyx measurements in the last test. Although presenting differences in the number of timeout communication errors, Pozyx working ranges remained about the same for the vineyard scenario which can be an important factor to deal with odometry errors. It also comes as a confirmation of the good balance between these two sources for a fusion algorithm.

The Pozyx Algorithm, in turn, showed some undesired outliers and unstable performance. Being based on the trilateration concept, it demonstrated to be more sensitive to the beacons placement. All in all, it can still be seen as a good alternative provided with good filtering

Future work regarding the ToF UWB localization system will include more intensively studies on the effect of the different UWB parameters as well as the antenna orientation and environment constraints (LOS vs NLOS). Having, for instance, a calibration phase to identify LOS and NLOS conditions would help to increase the confidence on range measurements. This better error and noise modeling would permit to expand the localization to larger and harder environments and higher working distances.

Furthermore, regarding the actual EKF localization some points could be part of future implementation:

1. Fusion of Odometry and Ranges with IMU data. IMU could serve as another reference for a better accuracy but also validate odometry measurements by detecting, for example, wheel slippage situations;

2. Test different outlier removal techniques like threshold by analysis of the mode or correlation with velocities given by other sources of information. Although the Mahalanobis Distance is usually employed for multivariate data, in the case of the Pozyx algorithm, different clusters of points were identified in some cases and the MD failed to remove the outliers;

3. More tests in the vineyard should be performed to get a more robust *in-loco* EKF parameterization. Different trajectories further away from the beacon's position can also be tested as well as measuring the performance of the Pozyx Algorithm (which wasn't done in the first test);

4. Adding more beacons to the system covering a wider range area and get a more redundant estimation;

5. Adding bearing measurements to the observation model in order to also have estimates of the orientation.

Finally, as previously mentioned, the higher complexity of the vineyard environment impacts the EKF performance. To deal with possible growing non-linearities introduced by this complexity and to have a more robust implementation against environment changes, an alternative filter, like a Particle Filter, can also be studied in the future.

Overall, this first work with Pozyx showed that it is a good and effective tool to improve the robot localization in a complex environment given its good accuracy/cost trade-off. This will help to increase the redundancy of AgRob or any other robot within a complex environment improving its localization accuracy. The still not so explored tools of the system can still help to better characterize the UWB technology and understand the effects of its configuration and the environment in the final localization.

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