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Localization in Constrained Environments

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Thesis

of the

École Doctorale Informatique, Télécommunications
et Électronique (Paris)

Localization in Constrained Environments

presented by

Trifun Savić

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requirements for the degree of

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in

Computer Science

at

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Presented on 22 September 2023.

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Acronyms

RTLS	Real-Time Localization System
IoT	Internet of Things
WSN	Wireless Sensor Networks
GPS	Global Positioning System
RF	Radio Frequency
LoS	Line of Sight
NLoS	Non Line of Sight
VLP	Visible Light Positioning
AoA	Angle of Arrival
RSS	Receive Signal Strength
RSSI	Receive Signal Strength Indicator
ToF	Time of Flight
ToA	Time of Arrival
ToT	Time of Transmission
TDoA	Time Difference of Arrival
TWR	Two Way Ranging
KF	Kalman Filter
EKF	Extended Kalman Filter
UWB	Ultra-Wideband
BLE	Bluetooth Low Energy
BLE LR	Bluetooth Low Energy Long Range
SoC	System-on-Chip
PPI	Programmable Peripheral Interconnect
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
ME	Maximum Error
MAD	Mean Absolute Deviation

Mojoj djeci, Irini i Danilu.

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Résumé

Cette thèse se concentre sur la **localisation à faible puissance dans des environnements contraints**, sans nécessiter d'infrastructure de localisation. Nous considérons deux cas d'utilisation cibles: la **localisation de bateaux** dans un port de plaisance, et la **localisation de robots mobiles** dans un environnement intérieur.

Nous commençons par évaluer deux systèmes de localisation en temps réel ("Real Time Localization System" en anglais, RTLS) basés sur les radiofréquences (Bluetooth Angle-of-Arrival et Ultra-Wide Band ranging). Leurs principaux inconvénients sont qu'ils nécessitent le déploiement préalable de points d'ancrage, et qu'ils ne sont pas à faible consommation, ce qui les rend peu compatibles avec nos cas d'utilisation cibles. Ce travail contribue à remédier à ces inconvénients en proposant deux nouveaux systèmes: WELOC et Blip. Nous proposons également RRDV, une solution de détection de rencontre de robots pour les systèmes multi-robots.

WELOC est un système de localisation basé sur les ultrasons qui réutilise les capteurs de détection de présence des bateaux déjà présents dans la marina. Il comporte un système de programmation qui déclenche l'émetteur-récepteur ultrasonique de chaque capteur de présence à des moments précis. WELOC présente le design d'un appareil mobile alimenté par batterie, capable de communiquer en toute sécurité à la fois par ultrasons et par signaux radio, et conçu à partir de composants disponibles sur le marché. Des essais en conditions réelles dans un port de plaisance dans le sud de la France montrent que l'appareil mobile peut être localisé avec une précision de l'ordre du centimètre, tout en étant à une distance de 10 m des capteurs de présence.

Blip est un système d'identification des bateaux dans un port de plaisance, qui ne nécessite qu'une mise à jour logicielle des systèmes de capteurs intelligents existants dans les ports de plaisance. Il utilise les informations fournies par les capteurs de surveillance des bateaux déjà présents (installés dans la cabine d'un bateau) et les combine avec les informations provenant de l'infrastructure fixe des capteurs de présence pour identifier les bateaux sur les emplacements. Lors de nos essais en conditions réelles, le système a fait preuve d'une précision de 100% dans l'identification des bateaux.

Cette thèse propose également **RRDV**, un système de détection de rencontres entre robots dans un système multi-robots. De nombreux robots sont déjà équipés d'un capteur à ultrasons pour mesurer leur distance à des objets devant eux. RRDV est une mise à jour logicielle pour ces robots, leur permettant d'utiliser ces capteurs à ultrasons pour détecter les rencontres avec d'autres robots. En testant RRDV sur un système multi-robots réel,

il détecte correctement 96.7% des fois où deux robots se font face pendant 5 s ou plus.

La thèse contribue au domaine de recherche croissant de la localisation et des communications sans-fil à faible consommation, en proposant des solutions innovantes pour des systèmes de localisation précis et à faible consommation dans des environnements contraints. Ces solutions ont des applications non seulement dans l'industrie maritime mais aussi dans les systèmes multi-robots. La thèse démontre l'efficacité des systèmes basés sur les ultrasons et met en évidence le potentiel du matériel ubiquitaire prêt à l'emploi pour le développement de systèmes de localisation.

Summary

This thesis focuses on **low-power localization in constrained environments**, without the need for localization infrastructure. We consider two target use cases: **localizing boats** in a marina, and **localizing mobile robots** in an indoor environment.

We start by evaluating two RF-based Real-Time Localization Systems (RTLS), based on Bluetooth Angle-of-Arrival and Ultra-Wide Band ranging. Their main drawbacks are that they require the prior deployment of anchors and are not low power, making them poorly compatible with our target use cases. This work contributes to addressing these drawbacks by proposing two novel systems: WELOC and Blip. We further propose RRDV, a robot encounter detection solution for multi-robot systems.

WELOC is an ultrasound-based localization system that re-purposes boat presence detection sensors already deployed in the marina. It features a scheduling scheme that triggers each presence sensors' ultrasonic transceiver at specific times. WELOC introduces a battery-powered mobile device capable of securely communicating with both ultrasound and radio signals, designed entirely from off-the-shelf components. Real-world tests in a real-life marina in the South of France show a mobile device can be localized with cm-level accuracy when it is up to 10 m away from presence sensors.

Blip is a system for boat identification in a marina, which only requires a software update to existing smart marina sensor systems. It uses the information from already installed boat monitoring sensors (mounted in a boat's cabin), and combines that with the information from the fixed infrastructure of presence sensors to identify boats on slips. In our real-world tests, the system exhibits 100% boat identification accuracy on the given dataset.

This thesis further proposes **RRDV**, a system for detecting robot-to-robot encounters in a multi-robot system. Many robots are already equipped with an ultrasound sensor for measuring the distance to objects in front of them. RRDV is a software update to those robots, allowing them to use those ultrasound sensors for detecting encounters with other robots. When testing RRDV on a real-world multi-robot system, it correctly detects 96.7% of the times two robots face one another for 5 s or more.

The thesis contributes to the growing research field of localization and low-power wireless by proposing innovative solutions for low-power and accurate localization in constrained environments. While these solutions have applications well beyond the ones outlined in this thesis, we chose the use cases of localization of boats in marinas and localization of robots in an indoor environment to remain perfectly focused. The thesis demonstrates the effectiveness of ultrasound-based systems and highlights the potential of ubiquitous off-the-shelf hardware for the development of localization systems.

Chapter 1

Introduction

This thesis contributes to the growing research field of localization and Internet of Things (IoT). Specifically, it focuses on the development of accurate, low-power localization systems in constrained environments, without the need for prior deployment of localization infrastructure. This chapter provides an overall introduction to the topic of the thesis and is organized as follows. Section 1.1 introduces the topic of localization. Section 1.2 describes the fundamental localization techniques. Section 1.3 presents the different localization technologies. Section 1.4 shows the types of localization architecture. Section 1.5 provides an introduction to IoT technology and its applications. Section 1.6 presents the two driving use cases of this thesis: localizing boats in a marina and localizing mobile robots in an indoor environment. Section 1.7 lists the contributions of this thesis. Finally, Section 1.8 details the organization of this manuscript.

1.1 Localization Primer

Localization is a technique for estimating the position of an object or a person in a certain environment. It is becoming a well-studied research field, with research publications and commercial products emerging to improve localization systems. Studies have been conducted in many areas, from the core technologies used in localization systems to positioning algorithms and signal processing [1].

Depending on the environment we can classify localization into two main categories: outdoor and indoor localization. Outdoor localization pertains to determining the geographical coordinates or position of objects, individuals, or devices within open-air environments, such as urban areas, rural landscapes, and natural settings. The most common technology for outdoor localization is the Global Positioning System (GPS), a network of satellites that orbit the Earth and transmit signals that can be received by GPS receivers. These receivers use the signals from multiple satellites to calculate their precise location. Indoor localization refers to the process of determining the location of an object, person, or device within an enclosed space, such as a building, shopping mall, or warehouse. Unlike outdoor environments, where GPS signals are readily available for accurate positioning, indoor spaces pose unique challenges due to the limited visibility

of satellites and the presence of obstacles that can disrupt signals. To overcome these challenges, researchers need to use other technologies, deploy them in the enclosed space, in order to enable localization.

Obtaining the location of a device or a user is essential to many applications, including in health care, industrial production, autonomous vehicles, smart cities, and smart buildings [2]. Health care applications such as clinical motion analysis, physiotherapy and rehabilitation strongly benefit from localization solutions. By installing sensors on a patient's body for tracking their body movements and micro movements, health professionals can significantly improve medical diagnosis and treatment [3], [4]. In case of the spreading of infectious disease inside the health care facility, contact tracing is essential in order to interrupt ongoing transmission and reduce the spread of an infection [5], [6]. Localization is extremely important in industrial facilities. In a manufacturing plant, we want to know the position of people, tools and materials inside a production line, which allows the development of indoor localization-based safety system [7]. Industrial facilities such as warehouses and other cluttered environments use robotic arms with sophisticated localization capabilities to perform retrieval tasks [8]. Another example application where localization is required are autonomous vehicles. Using a localization system, an autonomous car or a mobile robot is capable to estimate its pose in a map based on on-board sensors information [9]. In smart cities and smart buildings, knowing the location of a user and/or device paves the way for many new applications like public safety, tracking services and robot guidance (in-building) [10].

In the following sections, we introduce the most popular localization techniques (Section 1.2), present the technologies (Section 1.3) and details the types of architectures used (Section 1.4).

1.2 Localization Techniques

The localization *technique* is the way of estimating the position of the mobile device. There are many different localization techniques that can be combined with different technologies in order to develop a localization system. However, a specific localization technique usually gives the best results when combined with a particular localization technology. Thus, we need to carefully match these two fundamental elements of the localization system in order to meet the application requirements and have satisfying results. This section focuses on the most widely used techniques for low-power and low-cost localization systems. We introduce the following techniques: Receive Signal Strength (RSS) and fingerprinting, Time of Flight (ToF), Time Difference of Arrival (TDoA) and Angle of Arrival (AoA). Other techniques such Phase of Arrival (PoA) and Channel State Information (CSI) are not in the scope of this thesis. For detailed information about PoA and CSI localization techniques, the interested reader is referred to [11]–[13].

RSS-based localization is the most commonly used technique for the indoor localization. This is mainly due to market availability of low-cost and low-power System-on-Chip (SoC) that generate RSS readings through the Receive Signal Strength

Indicator (RSSI). The RSSI represents the value of the signal's power at the receiver side. The distance between the two devices or the radius of a sphere is calculated as the function of RSSI, where a larger RSSI value means a smaller distance between transmitter and receiver. The distance d between the two devices can be derived from (1.1) [14]:

$$RSSI = -10n \log_{10}(d) + C \quad (1.1)$$

In (1.1), n is the path loss exponent factor, C is a fixed constant. With one mobile device and at least three anchor devices, it is theoretically possible to obtain the 2D position of the tag using trilateration.

The biggest constraint of this technique is the poor localization accuracy due to the nature of the radio signals. Multi-path fading effects can severely affect the distance estimations, as the signal power at the receiver changes dramatically with slight changes of the mobile device's position and/or the environment conditions. When developing RSS-based localization solution using simulations, one must employ a suitable signal propagation model [15]. Some researchers use popular signal propagation models like Free Space Model (FSM) and Log Normal Shadow Fading (LNSM), while some design their own path loss models for specific use case [16]. In the case of real-world deployments, the environment changes over time. People move across buildings, furniture gets rearranged, Wi-Fi traffic changes. This results in dynamics of the wireless channel, on each of the communication frequencies. When evaluating RSS-based solution, we need to choose a testbed with dynamics in order to have good validity of our solution [17]. However, localization systems based on RSSI readings leverage their low-cost and low-power properties and they are a good choice for many applications. This technique is especially useful if the application requirements are proximity detection or the room-level localization accuracy. In order to improve the accuracy of the RSSI-based systems, researchers employ fingerprinting. This method comprises two phases: offline and online. In the offline phase, the RSSI readings at known locations are collected and stored. These readings are compared with the RSSI in the online phase to better estimate the mobile device's position. This method usually employs some machine learning method such as k-Nearest Neighbor (kNN), Neural Networks (NN), or Support Vector Machine (SVM). Although the fingerprinting method improves the accuracy of RSSI-based localization systems, it requires the knowledge of the environment and needs more computational power.

ToF is a technique where the distance between two devices is calculated as a function of the signal propagation speed and the time between the signal's transmission and reception. ToF is the difference between Time of Transmission (ToT) and Time of Arrival (ToA). When the ToF is calculated for the Radio Frequency (RF) signal propagation, the distance between the two devices is obtained by multiplying ToF measurements with the speed of light. In the case of sound-based localization systems, the ToF is multiplied with the speed of sound in the given medium. Fig. 1.1 illustrates the basic ToF calculation in the Two Way Ranging (TWR) method. Here, the initiator device sends a poll message for ranging to the responder, and records its TX time. The responder records its RX and TX times, and sends the message back to the initiator. The distance between the

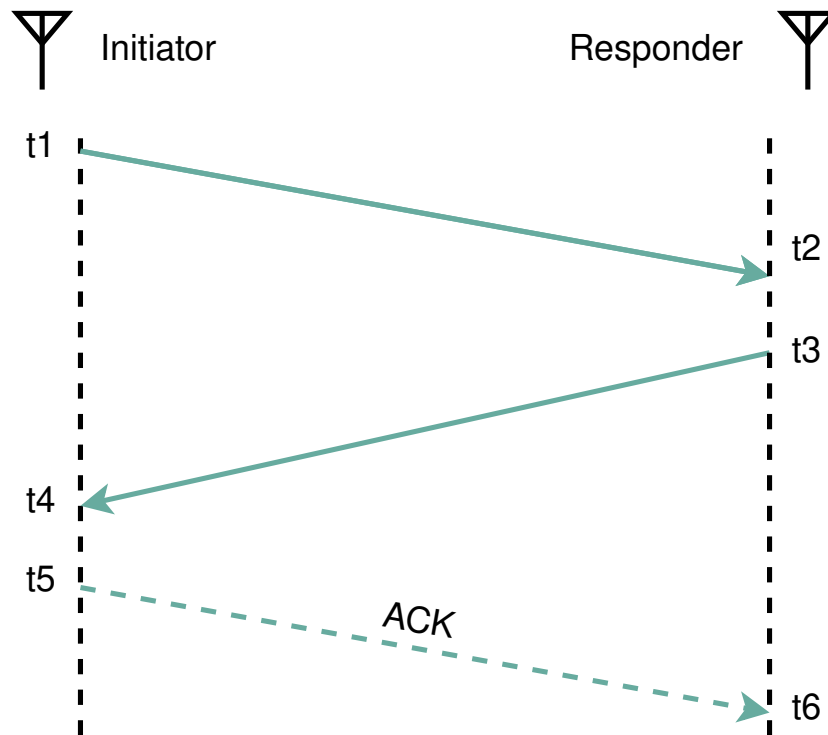


Figure 1.1: Time of Flight (ToF) technique.

two devices is calculated per (1.2).

$$d = \frac{(t4 - t1) - (t3 - t2)}{2}v \quad (1.2)$$

In (1.2), d is the distance between initiator and responder, v is the propagating speed of the signal, $t1$, $t2$, $t3$ and $t4$ are TX and RX timestamps shown in Fig. 1.1. The precision of the ToF calculation depends on many factors such as radio environment, sampling rate and drift of the local crystal oscillators. The latter is especially problematic when devices need to be time synchronized. In order to avoid the use of the precise time synchronization there are different ways of calculating ToF like Double-Sided TWR [18], where we can minimize the ToF estimation error induced by the crystal oscillators.

TDoA uses the relative difference in the signal's arrival time at the receiver side to calculate the device's location. *TDoA* is the core technique used in GPS for outdoor positioning and navigation. At least four anchor devices with known positions are needed to calculate the 3D location of the tag device. Unlike the TWR method, *TDoA* doesn't require full duplex communication between the tag and the anchors. What is needed is precise sub-nanosecond time synchronization between anchor devices [19].

AoA is a technique of estimating the angle at which the signal arrives at the receiver. In order to allow the calculations of the *AoA*, the receiver needs to be equipped with an antenna array, where the distance between adjacent antennas is less than half of the

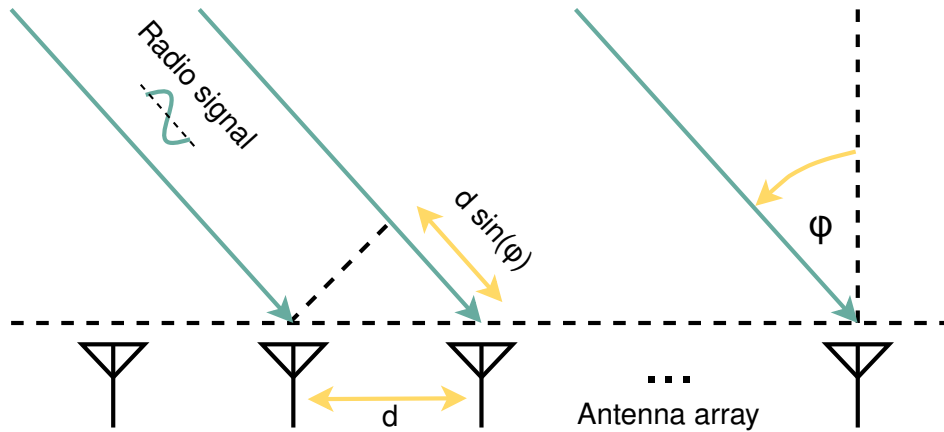


Figure 1.2: Angle of Arrival (AoA) estimation using antenna array.

signal's wavelength [20]. To obtain a 3D location of the tag, at least three antenna arrays at different locations are necessary, assuming the antenna array consists of antennas positioned in a line, per Section 4.2. Triangulation is then performed to obtain the location of the mobile device [21]. Fig. 1.2 illustrates how to calculate the AoA of the signal received by an antenna array. The signal's AoA φ is calculated per (1.3).

$$\varphi = \arcsin \frac{\alpha \lambda}{2\pi d} \quad (1.3)$$

In (1.3), λ is the wavelength of the incoming signal, α is the phase difference, and d is the distance between the two antennas. These types of the AoA estimations are constrained with complex RF design of the antenna arrays, multi-path propagation and larger localization error if the tag is positioned further away from the receiver. Another type of AoA estimation is used in lighthouse localization. In this technique, AoA is estimated by calculating the time between the synchronization laser pulse and horizontal and vertical laser sweep of the lighthouse. By knowing the angular speed of the laser sweep and the time difference between the pulses at the receiver, it is possible to calculate the angle of the receiver in reference to the lighthouse. For detailed explanation regarding this technique the readers are referred to [22].

A *Hybrid* localization approach combines the aforementioned techniques to improve the localization system. Typically, ToF and AoA are combined to improve the accuracy of the localization system. Combining these two techniques, a smaller number of anchor devices is needed to locate a tag in a 3D space. Even if the focus is not on having a smaller number of infrastructure anchor devices, fusing the measurements from the different localization techniques through the carefully selected filter (e.g. Extended Kalman Filter - EKF) could largely improve the localization accuracy.

1.3 Localization Technologies

The localization *technology* represents the physical “core method” used in the localization system.

Different localization technologies offer different capabilities and performance in terms of accuracy, range, battery life, availability and cost [23]. Depending on the application type and user requirements, the designer needs to choose the localization technology best suited for their needs. We divide the different localization technologies into three main groups, depending on the fundamental physical phenomena used. We introduce these technologies as light-based, sound-based and radio RF-based. Virtually all practical localization solutions use one of these physical phenomena at its core. There are numerous constraints when using these technologies for indoor localization. In this thesis, we focus on the low-power and low-cost technologies which are available on the market.

Light-based technologies use the optical and infrared part of the Electromagnetic spectrum. When used in the low-power indoor positioning systems, they are constrained with the reduced range of a couple of meters as well as with the LoS requirement, because light cannot penetrate obstacles. However, they usually offer millimeter-level localization accuracy, which makes them suitable for robot tracking and navigation applications as well as a high-speed data transfer, given their large signal bandwidth. Some of the most popular light-based localization technologies used in recent research are: Visible Light Positioning (VLP), Infrared (IR), and image-based localization.

- *VLP* typically uses photodiodes as a light source [24]. Multiple transmitters send beacons as light signals to the receiver. The receiver’s position is then estimated with respect to the transmitter’s locations, using RSS, ToF, TDoA, or AoA.
- *IR* technology is used in localization and tracking of resource-constrained mobile robots because of its millimeter-level accuracy and low-cost. As one of the representatives of this technology, lighthouse localization is used in Virtual Reality systems such as HTC VIVE [25]. Lighthouse localization uses IR lasers which sweep space in two different planes. The receiver device decodes the received IR pulse which contains the information about the current angle with respect to the lighthouse transmitter. The core concept of lighthouse localization was proposed by Römer *et al.* [26] in 2003 as a localization system for “Smart Dust”, cubic millimeter scale sensor nodes.
- *Image*-based systems such as Motion Capture use cameras to track the movements of objects with great precision, with some commercial systems reporting the positional error less than 0.3 mm and rotational error less than 0.05 ° [27]. These systems are usually used in the entertainment industry, sports science, medical applications, and animation [28]–[30]. The main disadvantage of these systems is their high price. In case of the OptiTrack motion capture system, a single motion capture camera can cost up to 6,000 USD, and in order to cover a space of $5 \times 5 \times 2 \text{ m}^3$, the system needs at least 8 cameras for animation applications [27]. Consumer camera-based localization systems include Azure Kinect [31], which

offers Computer Vision capabilities. This device allows for the development of the motion tracking applications at a lower cost [32], [33]. In the case of autonomous vehicles, mobile robots and drones the cameras are mounted on the mobile device to estimate its location in respect to the environment. Techniques like visual odometry are used in robotics and computer vision to estimate the motion of a robot or camera by analyzing the changes in its visual input, typically from one or more cameras [34]. While visual odometry focuses on estimating motion, it can be combined with other techniques like SLAM (Simultaneous Localization and Mapping) to build a map of the environment while tracking the robot's position within it [35], [36].

Sound-based localization systems use the speed of sound in the air and ToF to compute the distance between two devices. To locate a device, three or more anchor devices are required. A multilateration algorithm is used to turn distance measurements between the mobile device and each anchor into a location of that mobile device. Because the speed of sound is orders of magnitude lower than the speed of light, it allows the system to be less time sensitive to timing inaccuracy, and typically offers centimeter-level precision [37]. Similar to light-based technologies, sound cannot penetrate objects and walls. In a low-power setting, its range is limited to a few meters. In sound-based localization systems, the two common approaches are acoustic-based and ultrasound-based localization.

- *Acoustic*-based localization systems have the big advantage in the availability of microphone devices in smartphones. The ubiquitous microphones offer a great commercial opportunity, similar to Wi-Fi- and Bluetooth-based localization systems. Acoustic-based localization systems use the audible band of < 20 kHz and low-power audio signals, which should not be heareable. However, the big challenge is the signal reconstruction at the microphone, due to the sampling rate limitations and the signal's low power. Also, a big concern for the users could be the security and privacy issues, which need to be carefully examined.
- *Ultrasound* is the most common sound-based localization technology. Ultrasound uses frequencies above the hearing threshold of humans, which allows for a bigger transmit power to make them easier to detect on the receiver's side. Ultrasound-based localization solutions require synchronization, and thus these devices usually contain additional RF-based or light-based communication capabilities for time synchronization. There are some commercial systems on the market based on the ultrasound that allow the precise tracking of assets and people. One of these systems is offered by Marvelmind [38] which allows centimeter-level precision. Their devices include ultrasound transceivers and 915/868 MHz or 433 MHz radios for synchronization and communication. Both stationary and mobile devices are battery-powered but need frequent battery recharge, depending on the update rate. The longest operation time without recharging is around 1 month at 1 Hz update rate for a stationary device, and 12 h at 8 Hz update rate for a mobile device.

RF-based localization solutions are the most common and there is a big research interest in the last decade in this field. Different RF-based technologies are used in combination with different localization techniques in order to provide the necessary accuracy according to the application demands [39]–[41]. Despite the fact that light-based and sound-based technologies provide centimeter or even millimeter level precision, their biggest constraint is the LoS requirement and reduced range. RF-based technology can leverage the Non Line of Sight (NLoS) as well as the larger range to have more coverage and less infrastructure device “anchors” in the system. However, the accuracy of the RF-based systems can vary from 10 cm up to 100 m, mostly depending on the different RF-based technology they use. Predominantly, low-cost RF-based localization systems use Ultra-Wideband (UWB), Bluetooth, IEEE 802.11 (Wi-Fi) and IEEE 802.15.4.

- *UWB* is arguably the most precise RF-based technology used for indoor localization. It leverages the use of short pulses of sub-nanosecond duration with a large signal bandwidth of > 500 MHz, in the frequency range from 3.1 GHz to 10.6 GHz. These properties make the UWB signal less sensitive to multi-path effects, and allow the correct estimation of ToF, uniquely identifying the direct path of the signal [42]. Although its precision mainly depends on finding the first LoS path of the signal, UWB can also be used in NLoS scenarios if application requirements allow for a less precise localization accuracy. UWB technology has been present for over a decade in low-power personal area networks. It is recently included in some of the new smartphone devices which will make this technology more accessible. Recently, Apple launched a new tracking device on the market called AirTag [43]. This device combines UWB and Bluetooth technology for tracking, where UWB ranging and direction finding is available on the iPhone 11 or newer. The current leader on the market for providing UWB integrated circuits and modules is Decawave, with its DW1000 transceiver IC. Currently, many RTLS commercial solutions are based on the DW1000 transceiver, providing sub-meter localization accuracy [44]. In Section 4.4, we present a hands-on evaluation of one of the most popular UWB platforms, the Decawave DWM1001 containing DW1000 transceiver.
- *Bluetooth* has emerged as a major candidate for indoor localization due to its low power consumption, especially Bluetooth Low Energy (BLE) [45]. Most portable devices such as smartphones are Bluetooth-enabled and represent a great commercial opportunity for tracking and positioning applications as well as proximity detection. Although Bluetooth was mainly developed as a standard for communication, multiple localization and proximity detection applications leverage the Bluetooth radio. As an example, the availability of Bluetooth was extremely important for developing contact tracing applications during the health crisis of COVID-19 pandemic in France. The contact tracing application TousAntiCovid uses Bluetooth with proximity based techniques to detect whether the user had a close contact with a contagious person [46]. Although the aforementioned pros like low-cost, low-power and accessibility are very promising, Bluetooth-based

localization systems suffer from a limited accuracy. There are many commercial products like BLE beacons using RSS for proximity detection [47]. BLE beacons are broadly used in Wireless Sensor Networks (WSN), indoor/outdoor positioning and other low-power IoT systems. As a part of the Bluetooth 5 core specification, Bluetooth Mesh allows direct, dynamic connection between BLE beacons [48]. These networks provide low-power many-to-many communication capabilities and it can be found in localization applications such as: home and industrial automation, asset tracking and proximity detection. BLE beacons usually offer room-level accuracy, except when the system includes some fingerprinting method to allow for better accuracy. This method requires more computational power, environment information and human labor. Moreover, multi-path fading means that a small change in the environment such as a door being opened may require new fingerprints to be collected. On the other hand, some promising work was recently done on enabling ranging capabilities with BLE allowing for a meter-level precision. Link Labs introduced a firmware upgrade for enabling BLE ranging, called Bluetooth Xtreme Low Energy [49]. They claim a meter-level accuracy in 3D space, with 5-7 years of the tag battery life, depending on the update rate. Recently, a different localization approach is offered with the emerging BLE Direction Finding feature, with some companies claiming to have obtained 10 cm localization accuracy in their BLE AoA Real-Time Localization Systems (RTLS) solutions [50]. However, there are some constraints that the new BLE AoA estimation feature has, which will be presented in the Sections 4.2 and 4.3.

- *Wi-Fi* technology has similar constraints as Bluetooth when it comes to its localization capabilities. It was originally deployed for communication. Wi-Fi is ubiquitous, which makes it a great candidate for localization application. Many studies has been conducted on reusing the existing Wi-Fi infrastructure for indoor localization. However, Wi-Fi has a room level accuracy and not particularly low-power. Similar to Bluetooth, it could benefit from better accuracy if the localization solution includes fingerprinting together with carefully selected algorithms [51]. There are upcoming Wi-Fi standards that could be considered for future research in Wi-Fi-based localization, 802.11ax and 802.11ah [52], [53]. The former operates on 2.4 GHz or 5 GHz frequency bands and allows high-throughput in high-density settings such as stadiums, corporate offices and shopping malls. The latter operates on sub 1 GHz license-exempt bands. It provides low-power long range communication capabilities suitable for large scale sensor networks, which could be important to consider when designing localization systems that cover large areas.
- The *IEEE 802.15.4* standard defines the physical and MAC layer for low-cost, low-rate wireless personal area networks. It operates in license-free frequency bands at sub 1 GHz and 2.4 GHz. It is widely used in WSN to transport sensor data and actuator commands. The standard defines the function of measuring the received signal power in the form of RSSI. Therefore, a sink node can estimate

the location of an end device inside the network using statistical models based on measured signal propagation characteristics [54]. The IEEE 802.15.4 standard is the core element of many wireless network technologies such as: ZigBee, WirelessHART, 6TiSCH and Z-Wave [55]–[58]. These technologies have motivated new research in the indoor localization field, to expand device capabilities to add location information inside the IoT network. ZigBee technology adds routing and networking functionality on top of IEEE 802.15.4. This allows devices to function as routers, expanding the range of communication. Because ZigBee uses IEEE 802.15.4 as a baseline standard, it also has the ability to obtain RSSI information [59]. Cheon *et al.* [60] demonstrate the ToA estimation using ZigBee devices which could enable ToF-based positioning systems in WSN. Industrial WSN solutions like SmartMesh IP can benefit from device location estimation using RSSI. By employing similar techniques as with BLE beacons, low-power wireless mesh networks can provide a room-level localization accuracy [61]. Moreover, researchers in the indoor localization field could consider Z-Wave [62]. Z-Wave is mainly used by home automation systems to connect various smart devices and appliances. Unlike ZigBee, which operates in both sub 1 GHz and 2.4 GHz, Z-Wave devices operates only in license-free sub 1 GHz frequency band to avoid interference from other technologies like Wi-Fi. Devices that support this technology can form a mesh network with the limit of 232 connected devices.

1.4 Types of Localization Architecture

When designing a localization system, many considerations have to be made according with respect to the application requirements [63]. Certainly, one of the first aspects that needs to be examined is the *architecture*. Architecture constraints determine the top-level characteristics of the localization system. It defines what element knows the position of the mobile devices: the system or the mobile device. This consideration has a big impact on scalability and security. Having the mobile device determine its own position without relying on the localization infrastructure scales perfectly, as there is no additional cost to the localization infrastructure when going from 10 mobile devices to 1,000. This is the approach taken in Global Positioning System (GPS). The alternative is for the localization system to feature a centralized positioning engine which communicates with the mobile devices and is responsible for computing their location. This architecture approach is usually implemented in specific environments and applications, such as localizing assets in warehouses or tracking people in the hazardous environments.

In order to tailor the system to match the use case, the appropriate architecture approach is needed. We differentiate two architectures: *inside/out* and *outside/in*.

An *inside/out* approach allows the mobile device to know its position relative to the localization infrastructure. Usually, this approach requires the computation of the location directly on the mobile device, given the necessary data from the infrastructure. In the case of the localization of user/smartphone devices, the computational power of these devices is not very limited and the designer could implement “heavy” algorithms

for localization. For resource-constrained devices such as low-cost and small form-factor robots, this can be computationally challenging. In this case, the designer needs to carefully select the localization algorithm that suits the limited computational power of the device. This approach is primarily used for navigation of the mobile device. However, the end device can also report its location back to the localization system to display its position for the tracking purposes.

An *outside/in* approach is typically used in tracking applications, where the localization system tracks the mobile device and provides different services according to the application requirements. In this architecture, the localization infrastructure collects the necessary information from the mobile device. The location of the mobile device is then computed by the localization system. This architecture allows the tracking of a large number of devices, with extended battery life of the mobile device.

Inside/out and outside/in architecture approaches are depicted in Fig. 1.3.

1.5 The Internet of Things

The Internet of Things (IoT) is a rapidly growing network of physical objects or “things” that typically embed sensors, software and connectivity, enabling them to collect and exchange data. IoT is important because it has the potential to revolutionize the way we live and work by enabling seamless communication and automation between devices. The history of IoT can be traced back to the late 1990s, when the term “Internet of Things” is first coined. However, the idea of connecting physical objects to the Internet dates back even further, to the early days of the Internet itself. The development of wireless communication and sensor technologies in the early 2000’s enabled the widespread adoption of IoT, leading to the Fourth Industrial Revolution or Industry 4.0 [64]. This revolution is characterized by the integration of physical and digital systems, the use of big data and analytics, and the automation of complex tasks. IoT is a critical component of Industry 4.0, as it enables the collection and analysis of data from physical objects in real-time, allowing for greater efficiency, productivity and innovation.

An IoT network consists of electronic devices called “motes”, which are connected to one another and to a central gateway. These are battery-powered devices that communicate wirelessly. A mote can be either a sensor device that measures and collects data, or an actuator device that activates/deactivates other devices such as motors. A central gateway connects an IoT network to the Internet, typically with a dedicated cloud-based application [65]. This allows users to have, in near real-time, the data from the sensors or to send command to an actuator.

Applications benefiting from IoT technology are numerous and include smart homes, healthcare monitoring, industrial automation, and transportation systems. For instance, using a smartphone or tablet, one can control various appliances remotely, including lights, thermostats and security cameras. This feature allows homeowners to monitor their homes and adjust settings from anywhere in the world. Furthermore, connected devices can optimize energy usage in smart homes. A smart thermostat can automatically adjust the temperature to save energy when the homeowner is away, and readjust it

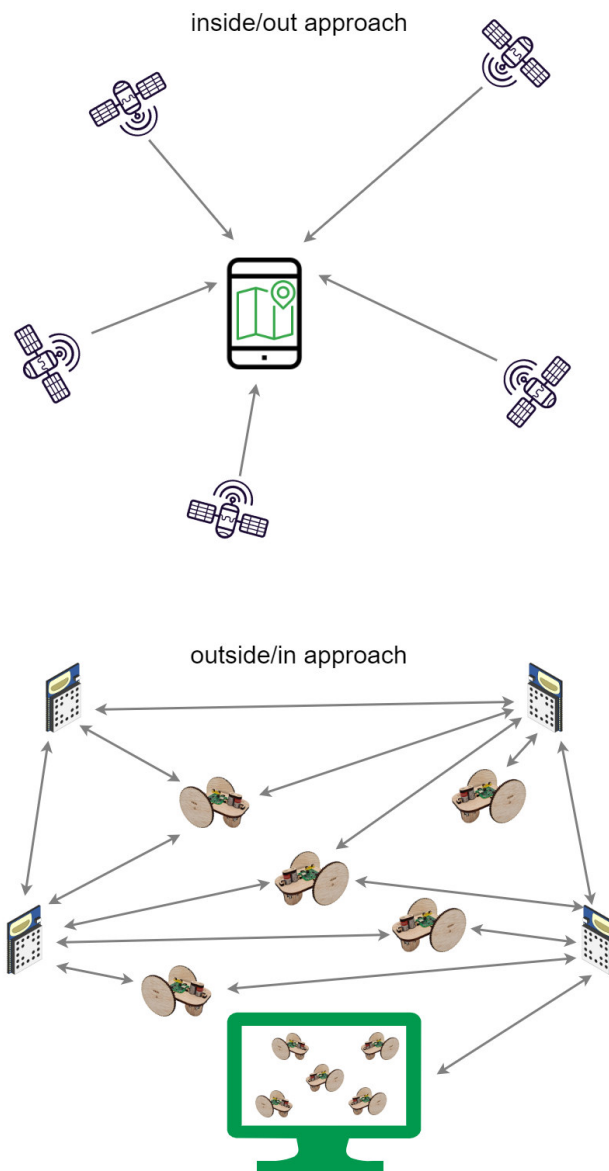


Figure 1.3: Localization architecture approaches: inside/out (top) and outside/in (bottom).

when they return. In healthcare, IoT devices have revolutionized patient care. By using remote monitoring devices, doctors can track patients' vital signs and detect health issues in real-time. This capability allows for early intervention and timely treatment, preventing health complications. IoT sensors have been instrumental in optimizing manufacturing processes in industrial automation. Sensors can collect data on various aspects of the manufacturing process, such as temperature, pressure and humidity, and use the information to adjust and optimize the manufacturing process. This optimization results in reduced waste, improved quality, and increased efficiency. Furthermore, in transportation, GPS tracking devices can monitor the location and speed of a vehicle, providing valuable data for fleet management. This data can be used to optimize routes and schedules, reducing fuel costs and improving delivery times. Sensors can also detect potential issues with a vehicle, such as low tire pressure, and alert the driver before a more severe problem occurs, thereby improving safety. These are just a few examples of the many applications of IoT that are already transforming various industries. The potential for IoT to bring about even greater innovations is immense.

Aside from their main role of being a sensor or an actuator device, it is important to know the exact location of the motes inside an IoT network [66]. Enabling localization capabilities in an IoT network opens many commercial opportunities, especially if we don't need to install additional hardware. However, determining the position of a device or system within its environment can be a challenging task. There are three main challenges when designing a localization system in IoT applications: localization accuracy, power consumption and the need for infrastructure. First, the aim is to achieve the highest possible accuracy in our localization system, given the application requirements. The accuracy of the system depends on the technology and technique used. For example, a motion capture systems can provide millimeter-level accuracy, but its implementation requires a costly and power-intensive camera infrastructure, limited range, and line-of-sight restrictions. Application requirements dictate which localization technologies and techniques are suitable. These trade-offs highly impact the accuracy of the system. Second, we want to reduce the power consumption of the tracking device to obtain years of battery lifetime and seamless operation. In order to stay low-power, we need to minimize the radio usage on the tracking device, by sending/listening for radio packets only a fraction of a time. Here, it is important to know the location update rate requirement in order to achieve the desired power consumption. Third, we do not want to introduce additional infrastructure inside an existing IoT network. We want to avoid the installation of new fixed devices. Ideally, we want to reuse the existing infrastructure of fixed wireless devices inside the IoT network.

1.6 Driving Use Cases

In this section we present the main driving use cases for this thesis. Section 1.6.1 introduces the concept of connected marinas and describes this first use case. This use case drives the research of low-power, infrastructure-free, localization systems with real-life marina requirements. Section 1.6.2 presents the second use case: indoor

localization of mobile robots. This use case drives the state-of-the-art survey of this thesis. It also sets the requirements for the development of collision avoidance solutions in multi-robot systems.

1.6.1 Smart Marina

Marinas are a fundamental part of the boating industry, providing a convenient and safe place for boaters to dock their vessels. These facilities provide a range of services to enhance the boating experience. The increasing popularity of recreational boating around the world has resulted in a surge in demand for marina services, making effective marina management and automation of its services critical for ensuring a seamless experience.

Managing a marina can be a complex task, involving the coordination of various stakeholders such as boaters, staff, and service providers. To effectively manage a marina, it is necessary to have robust systems and processes in place that can handle the diverse needs of its users. These may include boat navigation and tracking, dock reservation systems, monitoring of berth occupancy and energy consumption, among others. With effective management, a marina can operate efficiently and provide a safe and enjoyable environment for all boaters.

Today's marinas are quickly evolving, with many boat owners renting their boats through online platforms or living on them inside the marina throughout the year [67]. This leads to an increase in customer demand, and marina owners need to guarantee the safety of the boats and offer new services. As marinas evolve, their requirements change too. Marinas can leverage the power of embedded micro-controllers, low-power wireless communication, and sensors/actuators to offer an array of innovative services. IoT technology can be used to detect the presence of boats in moorings, track water and electricity usage on a per-boat basis, and monitor undesired events on a boat, in real-time. The best part is that this can be accomplished without the need to install any wires for power or communication. Installation can be completed in a matter of hours, and the absence of wires and cables allow seamless pontoon configuration changes inside the marina. These technologies help marinas transition from a simple docking spots for boats to smart marinas. Fig. 1.4 shows an example of a smart marina environment.

There are commercial IoT solutions on the market today that offer automated services to marinas. Falco is a company that creates such solutions in order to help marinas transition to smart marinas [68]. Falco creates devices for real-time boat monitoring, boat presence detection and electricity consumption. These devices are all battery powered and communicate with each other the radio, forming a low-power wireless network. This network includes a central gateway which forwards all the data generated by the IoT devices to the cloud. Also, Falco offers cloud-based digital solutions for both marina managers and boat owners. The work presented in this thesis is realized under a CIFRE agreement between the company Wattson Elements - Falco and the National Institute of Research in Computing and Automation (Inria).

One aspect of a smart marina that is particularly beneficial for marina managers and boat owners is the localization of boats and equipment inside the marina environment. By using a localization system, marina operators can monitor vessel traffic, prevent



Figure 1.4: Ecosystem of smart marina solutions [68].

overcrowding, and improve overall safety and security. It can provide valuable insights into user behavior, allowing marina operators to optimize their services and resources accordingly. It is clear that the integration of a localization system in a smart marina presents a tremendous commercial opportunity. However, designing such a system requires overcoming the research challenges that constrained environments – such as marinas – impose. Specifically, we want to test and deploy our solutions in the Sète marina in the South of France, which sets the following requirements:

- localization error of less than 1 m;
- location update at least every 5 minutes;
- deployed devices need to be both low-power and wireless;
- fixed infrastructure needs to be battery-powered with at least 3 years of autonomy.

These requirements prevent us from deploying RTLS solutions available on the market today, which, to the best of our knowledge, do not satisfy them.

It is clear that augmenting low-power IoT networks for marinas by enabling them to also localize the boats and equipment is tremendously interesting from a research and commercial point of view. From the research point of view, we need to address the challenges of designing an accurate, low-power localization systems in constrained environments, such as near sea/ocean areas. Because we want to stay low-power, accurate and wireless, we cannot use the localization technologies such as GPS, and networks that

might exist inside the marina such as Wi-Fi and Ethernet. On the other hand, there are indoor localization solutions that we could apply to our use case, but require the deployment of a dedicated infrastructure of “anchors”. We want to reuse the existing low-power infrastructure already in place, such as the Falco IoT networks, and provide a software/firmware-based localization solution, with minimal hardware development.

In this thesis, we focus on a localization system in a smart marina, which involves the deployment of motes on both pontoons and recreational boats. The primary objective is to accurately locate boats to ensure they are in the correct location, and to detect any unexpected movements that may indicate theft. We also want to enable the localization of equipment and people in the constrained marina environments. In order to design such system, we do not want to deploy additional devices to serve as localization infrastructure inside the existing IoT network. The objective of this research is to provide the fundamental building blocks to overcome the following research challenges: need for prior deployment of the infrastructure to enable localization, and to mains power that infrastructure. Naturally, it is clear that the research we conduct to satisfy the smart marina use case can be applied to other use cases, that go far beyond this application.

1.6.2 Mobile Robots

The recent research in multi-robot systems on autonomous driving, coordination and formation control enables the development of many applications, including exploration and mapping, search and rescue missions, warehouse automation and industrial production [69]–[71]. Mobile robots of different sizes, shapes and capabilities cooperate to perform complex tasks. In order to do so, it is essential that mobile robots know their position in respect to the infrastructure and/or other mobile robots. This requires a dedicated indoor localization system that is capable of determining the location of the robots. We use the indoor localization of mobile robots as a second use case for this thesis.

Depending on the algorithm used on the mobile robots, multi-robot systems are centralized or distributed. In a centralized system, the information collected by the robots is transferred to the central control unit for processing. The control unit also computes the path planing for the robots, taking into an account the inputs from a localization system. A distributed system allows for the computation of the robots’ positions and the processing of the gathered information to be performed locally [72], [73]. We also distinguish a hybrid and cooperative schemes where the information gathered from one robot is shared with the group of its closest neighbors to improve system performance [74].

As a specific application that needs indoor localization, we introduce the DotBot, a small form-factor low-cost mobile robot for educational and research purposes. The latest version of the DotBot is depicted in Fig. 1.5. Hundreds of these miniature IoT robots with networking capabilities are deployed as a swarm, and are used to develop swarm navigation algorithms, for example for exploration and mapping [75]. Accurate continuous localization of these robots is essential in order to give the swarm spatial context, and allow the mapping of a certain environment. This use case results in several constraints when trying to estimate the robot’s position. First, the cost of the localization



Figure 1.5: DotBot: a low-cost micro-robot for education and research on networking and swarm robotics.

system needs to be very low, as the total cost of a DotBot must be below 20 EUR. Second, sub-decimeter localization accuracy is needed to allow precise mapping. Third, the refresh rate of the DotBot's location has to be fast enough to match the movement speed of the robots, at least 10 Hz. Fourth, the scalability of this localization system is crucial, as there can be hundreds or thousands of DotBots in a swarm. Fifth, the low-power operation of the mobile device needs to ensure the continuous localization of DotBots for years. Finally, these robots need to be small in size to allow the mapping of the environment that is not accessible by people, have the ability to be easily integrated in an existing system and include a small wireless sensor for monitoring certain parameters.

The mobile robot use case in this thesis drives two main research components. First, we want to use the DotBot as a guiding application for the survey of the state-of-the-art in indoor localization. The idea is to take into account the constraints that this application places on such systems, and use them as our classification criteria for the recent academic research in the field. Second, we want to tackle the problem of mobile robot encounter detection in a multi-robot system. Since we want to deploy hundreds of DotBots in a

swarm, there is a high likelihood that they bump into one another. Therefore, there is a need for a system that can recognize when mobile robots meet one another, as they move in a swarm, having in mind the low-cost requirements of the DotBot. This system has to be complementary to the indoor localization system and prevent collisions between robots, in case the localization system fails or cannot localize robots accurately enough.

1.7 Contributions

The work presented in this thesis builds upon the related work that we present in the Chapter 2, addresses the identified open research challenges, and brings the following key contributions.

1. Since our work belongs to the domain of IoT and low-power wireless, we want to start our research by evaluating RF-based technologies for RTLS. IoT devices already present in the marinas communicate wirelessly, through radio, which could be used to enable localization. Bluetooth AoA and UWB ranging technologies emerged recently, and the academic research conducted using these technologies show promising results. This makes them a good candidate for our use cases. Therefore, we perform experiments with Bluetooth AoA evaluation kits (Nordic Semiconductor and Texas Instruments) and UWB ranging (Decawave). The results show the accuracy of these technologies, used as is, without additional filtering algorithms. The initial practical evaluation helps bridge the gap between theoretical potential and real-world feasibility, a crucial step in determining the practicality of these technologies in specific contexts such as marinas. These findings contribute to the existing body of knowledge in the field, helping researchers to build up an intuition regarding the performance of these technologies for localization, within IoT applications. This is presented in Chapter 4.
2. The main drawback with the solutions in the current state-of-the-art is that they require the prior deployment of anchors (which therefore form an infrastructure), and that they require mains powered anchors, which remain active all the time and therefore consume too much to be powered by batteries. In order to address one of the research challenges we identify from our survey of the state-of-the-art, we need to enable localization without installing additional fixed anchors. Furthermore, we want this fixed infrastructure to be battery powered, which is not the case with the RF-based commercial RTLS products, such as Bluetooth AoA and Ultra-Wideband ranging. Therefore, we propose WELOC, an ultrasound-based localization system that uses the existing boat presence detection sensors in the marina as fixed infrastructure. Since the existing IoT network inside the marina is time-synchronized over the radio, we propose a scheduling scheme to trigger each presence sensors' ultrasound at specific time. We design a mobile device from the off-the-shelf components capable of receiving/transmitting both ultrasound and radio. We achieve 3.5 cm mean absolute ranging error in laboratory testing, assuming perfect synchronization, and the maximum range of 10 m. We

demonstrate the ultrasound detection using the proposed mobile device in a real-life marina in the South of France. All devices used in this system are battery powered, use standardized and secure protocols for communication. This system fundamentally departs from conventional methods by harnessing existing boat presence detection sensors as an infrastructure, eliminating the need for fixed and mains-powered anchors. This shift to battery-powered infrastructure, with years of battery life, eliminates the need for a costly and power-hungry anchor deployment, addressing a significant limitation in the current state-of-the-art. This system is demonstrated in Chapter 5.

3. By combining information from the existing IoT devices installed on the pontoons and inside boats, we can allow boat identification in the marinas. Previously proposed WELOC enables the localization using the existing hardware but requires a dedicated tracking (mobile) device, deployed on a boat, to know which boat is located at which slip. For this reason, we go one step further and propose Blip, a system for boat identification in a marina, which is implemented solely in software/firmware. Blip uses the information from already present boat monitoring sensors (installed in the boat's cabin), and combine it with the information from the fixed infrastructure of the presence sensors to identify boats on slips. Thus, Blip doesn't require a dedicated mobile device to be able to determine at which slip the boat is located. We show that Blip is 100 % accurate on the given dataset and successfully identifies boats inside the marina. Building upon the foundation laid by WELOC, Blip eliminates the need for a dedicated tracking device on boats, making it a more cost-effective and practical solution. Leveraging the real-world dataset we show that it is possible to use Blip algorithm and perform successful identification, without introducing additional hardware to the IoT network. We use the RSSI readings from the motes for proximity detection, and combine it with the smart parking solution. Similar approach could be explored in other smart city applications. Smart parking for cars could incorporate Blip in order to identify a vehicle in a car park. Also, electric vehicles' charging stations could benefit from similar RSSI-based identification, to associate the station with the vehicle. Chapter 6 shows the proposed system.
4. As we mention in Section 1.6, the second driving use case for this thesis is the indoor localization of mobile robots. We want to be able to detect when the two DotBots are facing one another, in a swarm of hundreds of mobile robots. Therefore, we propose RRDV, a system for detecting the robot-to-robot encounters in a multi-robot systems. This is an ultrasound-based system – using similar techniques previously shown in WELOC – which could be regarded as complementary to a localization system. We tightly synchronize, over the radio, the triggering of the ultra low-cost, ubiquitous, ultrasound sensor, mounted on the mobile robot. Finding the cases when the difference in distance reported by the two robots is less than 1 cm we detect an encounter. The system achieves 96.7% accuracy when the robots are in front of each other for more than 5 s. This contribution

is particularly relevant in the context of swarm robotics and collaborative tasks involving mobile robots. Ultrasound offers several advantages, including low cost, ubiquity, and minimal interference with other sensing modalities commonly used in robots. The use of off-the-shelf ubiquitous hardware in RRDV is a key feature. This means that the system can be readily integrated into existing robot systems as a software update, provided they use ultrasound sensors for distance measurements. This ease of adoption enhances its practicality and potential for widespread use. Beyond its technical achievements, RRDV holds broader implications for the field of robotics. It addresses a fundamental challenge in multi-robot systems by providing an efficient means to detect encounters accurately. This capability opens doors to improved coordination, collision avoidance, and collaboration among robots, which are pivotal in applications ranging from warehouse automation to search and rescue missions. The RRDV implementation proposed in this thesis is open-source, with the source code provided on a public git repository. RRDV is presented in Chapter 7.

These contributions collectively advance the state-of-the-art in ultrasound-based localization, RSSI-based identification, and robot-to-robot encounter detection, offering novel and efficient solutions for a range of real-world applications. These contributions are grounded in robust scientific principles and methodology, significantly pushing the boundaries in the field of low-power localization in IoT. The practical implications of these advancements are far-reaching and have the potential to impact various industries and applications, from maritime safety and management to the coordination and cooperation of mobile robots in complex environments.

1.8 Organization of this Thesis

The remainder of this thesis is organized as follows.

Chapter 2 gives a use case driven survey on recent academic research related to this thesis. This work aims at identifying the appropriate technology and techniques suitable for developing low-cost, low-power localization system, capable of providing centimeter-level localization accuracy. We introduce a specific use case as a guiding application throughout this chapter: localizing a low-cost low-power miniature wireless mobile robot, DotBot. We define a taxonomy and classify academic research according to five criteria: Line of Sight (LoS) requirement, accuracy, update rate, battery life, cost. From the research conducted in this chapter, we identify and discuss the five most important open research challenges: lightweight filtering algorithms, zero infrastructure dependency, low-power operation, security, and standardization.

Chapter 3 presents the methodology used to develop and evaluate proposed solutions in this thesis. We explain why the hands-on approach is challenging and complementary to analysis and simulation in low-power wireless systems. We present the experimental

setup for each of the main contribution chapters of this thesis. We give a detailed description of the existing IoT network and devices in the Sète marina, that are used to develop WELOC (Chapter 5) and Blip (Chapter 6). Finally, we show the experimental setup for RRDV (Chapter 7).

Chapter 4 presents a series of hands-on experiments that we perform with the popular RF-based technologies, used in RTLS systems today. We conduct experiments with commercial products based on Bluetooth AoA and UWB TWR. More specifically, we use Texas Instruments and Nordic Semiconductor commercial AoA evaluation kits, and Decawave UWB evaluation boards. We perform experiments with the provided equipment as-is, experiencing first-hand the various constraints these technologies have. Obtained results allow us to develop an intuition for the accuracy in angle and ranging estimations of the mentioned commercial products.

Chapter 5 proposes WELOC, an ultrasound-based localization system for localizing objects in a marina environment. WELOC uses the already installed infrastructure of commercial IoT devices, fixed at each slip on the pontoons, used for boat presence monitoring. These devices are equipped with an ultrasound sensor, have known GPS positions and form a wireless, time-synchronized ($<15 \mu s$ synchronization error), mesh network around the gateway. Without impacting the main function of the smart parking system for boats, we propose a scheme to schedule when each ultrasound sensor is triggered. We design a mobile device, from an off-the-shelf ultrasound sensor, compatible with those already present in marinas. We synchronize the device with each ultrasound trigger in the marina, and collect the timestamped distance measurements. The location of the mobile device is then computed using trilateration. We test the ranging accuracy of the mobile device in the lab, where we achieve a 3.5 cm mean absolute error, with a maximum range of 10 m. We perform field testing for the ultrasound signal detection inside the marina, which is equipped with 471 presence sensors, one at each of its slips. We show that our mobile device successfully detects the ultrasound signal on the pontoons.

Chapter 6 presents Blip, a system for boat identification in a smart marina environment. Blip combines the data from wireless IoT sensors already deployed to determine which boat is located at each slip. We develop the system using the Falco IoT solutions for smart marinas. Our system only uses the existing IoT infrastructure inside the marina, thus introducing no additional costs and hardware complexity. Blip combines data generated by the two types of sensors: Falco Presence deployed on pontoons for detecting a presence of a boat on a slip, and Falco Boat installed inside the boats for detecting events like intrusion, fire, tilt and shock. We validate our system on a historical dataset from 10-Aug-2021 to 30-Nov-2021, from the Sète marina in the South of France. The results show that the Blip system is 100 % accurate, successfully identifying 8 boats, 34 times upon their entry inside the marina.

Chapter 7 proposes RRDV, a system for robot-to-robot encounter detection. We use a low-cost ultrasound sensor and time-synchronized mobile robots to detect when the two robots are facing one another. Ultrasound ranging is triggered by the control application on a computer. The application sends a ranging command to the gateway, which broadcasts it to the mobile robots over the radio. Robots synchronize their ultrasound trigger pin with the start of frame event and send back the notifications with measured distances using Time-Division Multiple Access (TDMA). The system then finds the encounters by searching for timestamps where the difference in distance reported by two robots is less than 1 cm. The current implementation achieves a 20 Hz ranging update rate. RRDV is validated experimentally using 5 mobile robots which are controlled by the users and moved randomly. We implement a Computer Vision (CV) algorithm for tracking mobile robots as they move and detect when they are facing one another. The results show 96.7% successfully detected robot encounters, when the duration of the encounter is more than 5 s.

Chapter 8 concludes this manuscript, lists the main contributions of this thesis and discusses the possible avenues for future work, including possible optimizations in the WELOC protocol (which we call WELOC 2.0), and discusses applications benefiting from RRDV.

Chapter 9 presents a list of the publications, patents, entrepreneurial contributions, and software contributions that I made during the period of this thesis.

Chapter 2

State of the Art

Parts of this chapter were published as part of the following article: *Constrained Localization: a Survey*. [Trifun Savić](#), Xavier Vilajosana, Thomas Watteyne. **IEEE Access**, volume 10 (2022): 49297-49321.

Key Takeaways: This chapter gives a use case driven survey on recent academic research related to this thesis. This work aims at identifying the appropriate technology and techniques suitable for developing low-cost, low-power localization system, capable of providing centimeter-level localization accuracy. We introduce a specific use case as a guiding application throughout this chapter: localizing a low-cost low-power miniature wireless mobile robot, DotBot. We define a taxonomy and classify academic research according to five criteria: Line of Sight (LoS) requirement, accuracy, update rate, battery life, cost. From the research conducted in this chapter, we identify and discuss the five most important open research challenges: lightweight filtering algorithms, zero infrastructure dependency, low-power operation, security, and standardization.

2.1 Introduction

This chapter provides a comprehensive deep-dive into the state of the art of the recent academic studies, a discussion on the important lessons we learn from the survey, and a clear understanding of the open challenges and trends to expect in the next 3-5 years. We introduce a use-case driven survey and quantify the requirements of a specific application that needs localization. To satisfy the requirements we need to employ a suitable technique and technology. There are many localization techniques available, all having different constraints in terms of line-of-sight deployment, update rate, accuracy, battery lifetime and security [76]. It is important to be able to navigate the trade-offs to find the best match between the application and localization system.

In order to design a localization system that overcomes the constraints that we identify in our DotBot use case (Section 1.6.2), we need a thorough analysis of the state-of-the-art in the field of indoor localization. We therefore identify the latest technologies and techniques suitable for being used in low-cost and low-power systems, capable of providing accurate, low-power localization. Specifically, we provide an up-to-date survey of the academic papers on indoor localization that were published from 2015 to 2022.

This chapter is organized as follows. Section 2.2 presents the classification criteria that we choose for classifying the recent research on indoor localization. We introduce five criteria: *Line of Sight (LoS) requirement, accuracy, update rate, battery life and cost*. Section 2.3 surveys the recent academic research on indoor localization. We introduce the works based on different technologies organized in three groups: light-based, sound-based and RF-based. We also discuss the lessons learned from this survey and talk about the complexity in localization systems. Section 2.4 highlights some of the main open research challenges in indoor localization. Finally, Section 2.5 summarizes this chapter.

2.2 Taxonomy - Classification Criteria

In this section, we propose classification criteria for the recent academic research on indoor localization. We introduce five different criteria: LoS requirement, accuracy, update rate, battery life and cost. These criteria allow us to classify the recent work on indoor localization in academia, and better understand what the constraints of their solutions are with respect to the metrics mentioned.

2.2.1 Line of Sight Requirement

The LoS requirement is probably the biggest constraint for the light-based and the sound-based localization systems. Given their nature, signals can't penetrate walls and obstacles and require a direct LoS to work properly. For the RF-based systems, LoS is also favorable but the NLoS ranging could also be exploited [77]. Even though the LoS requirement is mainly determined by the type of fundamental technology used, it can be also required by an application.

2.2.2 Accuracy

The accuracy of a localization system is typically the main requirement of any localization application. As one of the most important characteristics of the localization system, good accuracy is needed for the tracking and navigation of a user/device in a certain environment. The accuracy of a localization system depends mainly on the technology constraints, as well as on the careful selection of localization algorithms to estimate the position of the mobile device. Some light-based technologies offer millimeter-level localization accuracy, while some RF-based technologies like Low-Power Wide-Area Network (LPWAN) [78] offer 100 m localization accuracy. For evaluating the localization accuracy authors usually employ metrics such as: Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Maximum Error (ME) and Mean Absolute Deviation

(MAD) [79]–[81]. Although different applications have different accuracy requirements, in this survey we will treat a sub-decimeter level accuracy as the precise localization.

2.2.3 Update Rate

RTLS systems typically require fast location updates without significant delays. Depending on the application this could be of crucial importance. In industrial monitoring applications, fast location updates from the autonomous robots or conveyor belts are needed to ensure safe operation. Unlike industrial environments, asset location for tools or medical equipment is usually reported when the asset moves from its original position. Even in these applications, a periodic location update every couple of minutes is needed in order to ensure that the asset is in its right position.

2.2.4 Battery Life

Energy efficiency is one of the crucial features for any localization system. The user should be able to use the system without needing frequent battery replacement on the devices that need to be located. Many systems offer the possibility of rechargeable batteries on the mobile devices, but this is not convenient for most tracking applications that need the system to run continuously. In the best case scenario, the localization system needs to offer several years of battery life, where the careful trade-off should be made between localization battery life and update rate, according to the application requirements.

2.2.5 Cost

An important aspect of any localization system is its cost. Nowadays, many semiconductor companies offer a localization-enabled low-power chipsets, that could be integrated in everyday devices. The exploitation of connectivity and sensing together with the localization possibilities inside the single low-cost device opens up a wide range of new applications.

2.3 Academic Research on Indoor Localization

A good body of publications related to indoor localization has emerged in the recent years. Several survey articles provide a deep analysis of the research advances in this field.

Some survey papers focus on a specific technique. Alarifi *et al.* [82] present a thorough analysis of UWB-based localization systems. The authors discuss UWB positioning systems from the perspective of different techniques used in the development. Yang *et al.* [83] present a survey of academic work done on using the inertial sensors in smartphones in order to assist/enable localization. The authors put a particular focus on combining inertial sensors with Wi-Fi fingerprinting. Gu *et al.* [84] give a review of the work conducted in improving the indoor localization with a spatial context. The authors focus on spatial context in the form of maps, grid models, graph models and landmarks.

There are a number of survey papers which provide a more general overview of indoor localization. Xiao *et al.* [12] present a survey on indoor localization from the device perspective. Authors review the research done on device-based and device-free indoor localization. Device-based localization requires a user or a target to carry the locating device, whereas the device-free localization monitors the changes in the wireless signal without any device attached to the tracking object. Laoudias *et al.* [85] provide a detailed overview of the enabling technologies for localization, tracking and navigation in wireless networks. The authors discuss solutions and algorithms in areas such as: cellular network localization, Wi-Fi-based localization, range-free localization, data fusion, vertical positioning, mobility state estimation and indoor mapping. Zafari *et al.* [66] provide a deep analysis of different indoor localization techniques and technologies. The authors present different research papers on indoor localization, dividing them into two main categories: monitor based localization and device based localization.

This rest of this section surveys recent academic research on Indoor Localization. The works are grouped by fundamental technology used: light-based 2.3.1, sound-based 2.3.2, RF-based 2.3.3. In order to summarize and discuss research results, in Section 2.3.4 we present the main lessons learned from our study and provide a discussion on complexity of the localization systems.

2.3.1 Light Based Localization

Aswin *et al.* [86] present a localization system using visible light as its fundamental technology. The LEDs transmit Manchester encoded messages previously stored in an MSP430 microcontroller. For calculating the receiver's position, the authors use four synchronized transmitters to transmit in a Time Division Multiple Access (TDMA) scheme. The communication data rate is set to 20 kbps due to limitations of the receiver. Localization information is obtained by measuring the RSS from all four transmitters. Experimental validation is done by having a labeled area below the transmitter as a 4×4 matrix (87 cm x 87 cm), with 1.6 m between the transmitters and receiver. The system needs to be trained several times by putting the receiver in each matrix cell to record the RSS of the transmitters. Position is then calculated by the probability of occurrence. The authors indicate this system has sub 1 m accuracy in experimental conditions. They also provide an image processing based localization method using a camera to localize the transmitters, which is not integrated in the prototype of the system.

Kilberg *et al.* [87] present the localization of the quadrotor using bearing estimations from deployed nodes at known positions. The quadrotor is equipped with a planar laser, a 9-axis Inertial Measurement Unit (IMU), a 802.15.4 radio, and an optical flow deck and z-ranging infrared sensor for velocity and altitude measurements. Deployed nodes are equipped with an IEEE 802.15.4 radio and a photodiode that receives the IR light from the planar laser on the quadrotor. The system is using OpenWSN, Time-Slotted Channel Hopping (TSCH), as a synchronized time base. The lighthouse quadrotor rotates while recording its heading-timestamp information. Anchor nodes detect the laser sweep and record the network-synchronized timestamp. The lighthouse robot periodically broadcasts its timestamp-orientation mapping to anchor nodes. Anchor nodes use the

received timestamp-orientation broadcasts and previously stored timestamps from the laser sweep to calculate their bearing relative to the quadrotor. Each anchor node then sends that relative bearing back to the lighthouse quadrotor, which uses it to localize itself. The authors use the Extended Kalman Filter (EKF) on the Crazyflie for state estimations. The experiment is performed in a motion capture room using the OptiTrack system for capturing ground truth information with sub-millimeter accuracy. The reported RMSE for the position on the x axis is 0.57 m, the RMSE for the position on the y axis is 0.39 m. This error is measured after the filter converged (after 175 s). Over the duration of the experiment, the gyroscope drift accumulated to 20 degrees of error near the end of the quadrotor's flight. The pose was estimated using the stock Crazyflie EKF algorithm, which relies on the gyroscope measurement data. The measured bearing error bias (mean error) is 19.5° , with a standard deviation of 24.7° . The authors report that this error is larger than expected, and that a likely cause of error is the timing error introduced by the firmware interface between the wireless sensor node performing measurements and the Crazyflie. This system could also be used with nodes with an unknown position.

Kilberg *et al.* [88] present a lighthouse-based localization system for localizing a crystal-free single-chip micro mote, called SCuM. Lighthouse localization insures that the form factor of the SCuM chip is not changing by using its optical receiver not only for programming but also for receiving IR pulses from a lighthouse base station. The SCuM chip computes its azimuth and elevation relative to the base station. The authors use two base stations in order to determine the 3D position of the mote using a Direct Linear Transformation and triangulation. SCuM reports its azimuth and elevation to the OpenMote board connected to the PC. The position is calculated on the PC. The system is evaluated using the OptiTrack sub-millimeter tracking system as ground truth. When clear outliers are removed in post-processing (errors bigger than 10°) the 3D triangulated tracking data gives the mean absolute error of 1.54 cm, 1.50 cm, and 5.1 cm for the x , y , and z axis, respectively.

Campos *et al.* [22] describe the use of the lighthouse localization with EKF in the conveyor belt industrial application. The transmitting node is located on a conveyor belt containing an open-source wireless sensor mote MIMSY [89] and an optical receiver module for receiving IR laser sweep from the lighthouse. When the node enters a predefined unsafe zone on one side of the conveyor belt, a message is sent to the receiver circuit which reverses the DC motors. The process is repeated when the cart reaches the unsafe zone on the other side. The lighthouse base station is located 3 m from the cart. The system exhibits as less than 1 mm precision over 1 M azimuth samples. The update rate for the EKF is 1 kHz, the same as the sample rate of the accelerometer. Results show that median overshoot (after entering the unsafe zone) is 9.9 mm for lighthouse only, and 1.1 mm when using EKF. The standard deviation for lighthouse only is 10.9 mm and 0.8 mm for the EKF. The median latency of the lighthouse localization only is 26.7 ms, 3 ms for the EKF. The use of an EKF and accelerometer allows the position estimation in NLoS conditions when there is an occlusion. The authors report that, when no part of the conveyor belt is occluded from the lighthouse base station's IR sweeps, the position

estimate at the unsafe zone boundaries has a median standard deviation of 0.109 mm. In the case where half of the conveyor belt is occluded from the base station, the EKF reports a median position estimate standard deviation at the occluded boundary of 0.875 mm.

Yan *et al.* [90] describe CurveLight, IR light-based indoor localization solution. In the proposed system the transmitter consists of an IR LED, covered with a hemispherical shade that rotates, and a receiver that detects the light signal with a light sensor. The key element of the system design is a set of curves that define different regions on the shade that covers the transmitter. The shade rotates at 1200 revolutions per minute (RPM) and it is mounted on a ceiling at a known height, with LED flashing at 22 KHz rate. When the shade is rotating the transmitter generates a unique light signal, for each part of the area below the transmitter, due to the curved design of the shade. The transparent regions of the shade allow the light to pass without intensity loss and translucent regions that reduce the intensity of the IR. The receiver then decodes the light signal and calculates its angle in respect to North and radius because different radius corresponds to a different length of the gray arc (curved region with lower light intensity). The Kalman Filter (KF) is then used to further improve the localization accuracy. Authors test the proposed system in indoor environment and production deployments. In the indoor environment the system achieves 2-3 cm average location error with an update rate of localization of 36 Hz. In case of a real-world deployment such as autonomous car parking system authors report the mean localization error of 3.5 cm.

2.3.2 Sound Based Localization

Qi *et al.* [91] present a localization system based on ultrasound ToF measurements. The system consists of a server, multiple sensor nodes (anchors), and mobile robots that need to be localized. Each sensor node has two radio chips, a CC3200 for communication, a CC2500 for synchronization. The Least Squares Method is used to detect the envelope of the ultrasound signal. The authors report a 1 μ s synchronization error between nodes, where only two nodes are exchanging messages. The reported mean distance error in the experiment is 0.6 mm for 1 m distance and 1.4 mm for 3 m distance between devices, in LoS conditions.

Esslinger *et al.* [92] present three optimization approaches for improving ultrasound ToF-based systems. The authors verify these optimization approaches by using mobile devices equipped with ultrasound transmitters and anchor devices equipped with ultrasound receivers. Mobile and anchor devices are also equipped with IR photodiodes used for time synchronization. The prototype allows tracking of multiple objects simultaneously by applying virtually orthogonal Gold codes to the carrier signals in a Code-Division Multiple Access (CDMA) environment with the capacity of 127 transmitter devices. Gold code sequences are statistically uncorrelated and allow the use of the same frequency, resulting in less interference and better utilization of the available bandwidth. It takes 63.5 ms to transmit the entire Gold code. As first optimization approach, the authors present the adoption circuit at transmitter and receiver, and report an increase in 3 dB bandwidth by a factor of 7.2 and 12.2, respectively. The median distance measurement error is -4.18 cm without the adaption

circuit, at 5.0 m. Applying the adaption circuit reduces the median error to 0.83 cm. In second optimization approach the authors present two mitigation strategies for reducing these spectral leakage effects caused by Analog-to-Digital Converter (ADC) sampling. Without any spectral leakage mitigation, the maximum absolute distance measurement error is 21.2 mm. The authors examine two approaches to reduce spectral leakage: circular correlation with multiple replicas having a different phasing, and envelope calculation in the circular correlation. Both approaches reduce the maximum absolute distance measurement error by 66.5%. However, authors report that the envelope calculation by Hilbert transform reduces the computational effort compared to the usage of multiple replicas. Finally, the authors propose an efficient circular correlation computation on Field Programmable Gate Array (FPGA). The real-time implementation of circular cross correlation shows that the distance measurement deviates with a median of 1.25 mm and has a variance of 5.57 mm.

Rekhi *et al.* [93] propose CRADLE, which combines RF and acoustic localization for ranging of passive tags. The system consists of a reader and a tag. The reader is capable of transmitting/receiving RF signal and transmitting ultrasound signals. The tag is equipped with an ultrasonic transducer connected to the RF antenna. The reader transmits the RF signal at a certain frequency together with an ultrasound signal. The ultrasound signal reaches the tag's ultrasonic transducer and excites it. This varies the transducer's capacitance and modulates the load of the tag's RF antenna. This creates sidebands which are then detected by the reader in the re-radiated RF spectrum. By demodulating the RF signal, the reader can extract the time when the passive tag received the ultrasound pulse. The reader computes the distance to the tag using the time it took for the ultrasound pulse to reach the tag. The tag's transducer is a precharged capacitive micromachined ultrasonic transducer (CMUT). The tag is completely passive and doesn't require battery power or energy harvesting for normal operation. The proof-of-concept of this system was tested in the outdoor environment with the distance from 1 to 6 m between the tag and the reader. The authors report a sub-decimeter level ranging accuracy, except at 2 m distance between devices where the error was above 10 cm. A possible application is lower cost motion capture systems. The future work outlined includes further miniaturization of the tags, enabling the tag's instantaneous velocity calculation using Doppler effect and making tags more isotropic.

2.3.3 RF Based Localization

Nandakumar *et al.* [94] present the localization of a backscatter tag with ultra small form factor that is able to run for 5-10 years on a coin cell battery. The tag can communicate at three frequencies: 900 MHz, 2.4 GHz, 5 GHz. The proposed approach is to use Chirp Spread Spectrum where the Access Point sends chirps on three frequency bands. The tag offsets the signal and backscatters it to the AP, which extracts the range information from the phase of the signal. The tag is designed using off-the-shelf components (microcontroller, RF switch...). The AP is designed using multiple software defined radios configured as transceivers. The authors use Non-Linear Least Squares to compute the 3D location. Multiple experiments are conducted to verify the accuracy

of the localization, both in a lab setting and in real-world deployments in houses and hospitals. The localization error varies from 2 cm to 145 cm at distances from 1 m to the maximum 60 m between the tag and the AP. Authors report good performance in NLoS conditions, with a localization error of 33 cm at 20 m distance. In the real-world single-story apartment deployment, this system achieves an accuracy of less than 30 cm. For two multi-story apartment deployments, the system achieves an accuracy of 60 cm and 1.2 m. When deployed in a hospital, the mean accuracy is 35.12 cm across all locations, with localization accuracy being proportional to the distance. The system can support multiple tags by having each tag shift the signal by different frequencies.

Ahmad *et al.* [95] present a localization system for passive backscatter tag-to-tag networks. Most backscatter tags utilize active receivers, whereas in the passive tag networks the tags are able to communicate by backscattering the signal between them. Communication between the passive tags can only exist in the presence of the external excitation signal. In this work authors develop a phase-based technique to perform ranging between the two passive tags. The ranging estimation is performed as a two-step process, estimating the amplitude and the phase of the signal and then extracting the range information from the signal's phase. The passive tag consists of a dipole antenna, 10-channel RF switch as a backscatter modulator, controlled by a microcontroller, a passive envelope detector demodulator and an 16 bit 1 Mbps ADC. The tag also contains USB interface and SD card for data collection. For evaluating the performance of their solutions authors use RF signal generator as the exciter to provide the RF signal to passive tags, operating at 915 MHz. The tags are positioned on a rail, at 1.5 m distance from the exciter antenna. Authors estimate the channel phase for tag-to-tag distances up to 2 m, repeating measurements 100 times at each distance. Authors report very small variations in phase within a few degrees with median ranging error of <1 cm. In order to evaluate localization performance authors propose the iterative likelihood-based technique, to extract exact the distance from the "wrapped" range estimation, due to the phase wraparound every 2π . Authors report a median localization error of <1 cm and the 90-percentile accuracy of <1 cm.

Yang *et al.* [40] use Wi-Fi Access Points (AP) with multiple antennas as anchors in their indoor positioning solution. They estimate the tag's position through a combination of ToA with AoA. The mobile tag is a Wi-Fi-enabled device with a single antenna, and can be a smartphone or a tablet. For measuring ToA, the Wi-Fi AP sends multiples of the same predefined message to overcome the width constraints of the Wi-Fi bandwidth. The signal reconstruction relies on finding the sample of a message that is closest to the arrival signal. For measuring the AoA, the mobile phone sends multiple messages toward the Wi-Fi AP, where the AoA is measured by using channel estimation technique, taking advantage of the AP multiple antennas. In this approach, the Wi-Fi AP acts as the initiator and sends the bursts of messages to the receiver (smartphone). After it receives the signal back from the smartphone, the AP calculates the ToF and AoA. The proposed solution is verified through simulation, where authors assume the following: when using only one AP the hybrid technique ToA/AoA is used, otherwise only AoA is calculated and position is obtained with triangulation. The authors consider a scenario where the

SNR is 20 dB, and the Wi-Fi AP's maximal indoor communication distance is 50 m. Using 10 predefined messages, a single Wi-Fi AP can achieve 2.2 m and 1 m positioning range for 20 MHz and 40 MHz bandwidth, respectively. With multiple Wi-Fi APs, the position range is 2.2 m and 0.5 m, respectively.

Yu *et al.* [96] introduce a localization system that uses the inertial sensors built into a smartphone together with the Wi-Fi Fine Time Measurement (FTM) protocol and RSSI to track pedestrians in an indoor environment. The authors present the use of an Adaptive EKF to fuse triaxial data acquired from the accelerometer, gyroscope, and magnetometer to compute the pedestrian's real-time speed and heading information. This work combines the RSSI and Round Trip Time (RTT) of the signals acquired from the local Wi-Fi APs to allow more accurate Wi-Fi ranging and proximity detection. The results of proximity detection are used to provide the absolute altitude reference to the barometer-based altitude calculation. Based on the results of the Adaptive EKF, the Wi-Fi ranging, and the proximity detection, a real-time Unscented Particle Filter (UPF) is applied to fuse all these results. The sampling rate of the built-in sensors is 100 Hz and 4 Hz for the Wi-Fi FTM. The real-time location update rate is 4 Hz. The heading calculated by the gyroscope drifts by about 30° after walking for around 20 min, while the fused heading drifts by only 4°. The fused RTT and RSSI gives the Wi-Fi AP-based landmark detection errors in range from 0.25 m to 0.64 m, with a median error of 0.4 m. The 2D positioning performance is given with Cumulative Distribution Function (CDF) where the positioning error within 1.11 m at 67.5%. The altitude error is within 0.28 m at 67.5%.

Alletto *et al.* [97] design a localization assisted interactive guide to a smart museum environment. It has three main components: a localization service, an image processing function and a cloud-based processing center. For localization, the authors use BLE beacons pre-deployed in each room of the museum, providing room-level accuracy. The smartphone-like device the visitor carries receives frames from the beacons and uses their RSSI to determine the visitor's location in the museum. This information is then passed to the processing center to be used by different services. This room-level information helps speeding up computation time and saves battery power as the images taken from the wearable device are compared only to the dataset of the artwork located in that particular room. The localization system also serves to detect the number of visitors in front of the artwork. If the number of visitors is smaller than a defined threshold the processing center sends the audio information about the artwork. Otherwise, the processing center provides the relevant artwork information to the interactive wall inside the room. As a localization part of the real experiment performed in the museum authors consider two scenarios. In the first scenario the BLE infrastructure devices are placed in NLoS, on the wall separating two rooms. In the second scenario the BLE devices are placed in LoS at 5 m from the separating door. Results show that the localization estimation was optimal in the first scenario, with a wearable device located at three different positions, at 0.5 m, 1 m and 3 m from the separating door. For the second scenario the results show lower localization probability when the wearable device is placed closer to the separating door.

Fragher *et al.* [98] evaluate BLE fingerprinting with static BLE beacons located

at known locations, using two approaches: single point position and tracking. Three advertisement BLE channels are used to gather RSSI information. These channels are associated with different gains and multi-path effects, due to their narrow width and wide spacing. The authors use iPhone's iOS 7 or above, which indicates on which channel the message is received. The positioning algorithm consists of fingerprinting, map construction and position computation. The fingerprinting approach is evaluated by deploying 19 beacons in a 600 m² building floor, and measuring the RSSI to the beacons. At first BLE beacons transmit at 50 Hz at 0 dBm. The iPhone is used to log the BLE beacons. In parallel, an Android 4.4.2 device gathers the RSSI of the Wi-Fi signal received from three APs. The localization is compared to ground truth gathered using an "Active Bat" system [99] which offers 3 cm accuracy, synchronized using a Network Time Protocol (NTP) server. The update rate of 10 Hz was found to be optimal, giving similar results compared to higher update rates. The best performance is achieved when 8-10 beacons are used per fingerprint. Lowering the transmit power to -15 dBm still provided good coverage for a reasonably low number of beacons. Authors report that their deployment of one beacon per 30 m² gave accuracies of < 2.5 m 95% of the time. Lowering the density to one beacon per 100 m² degraded gives accuracy of < 5.5 m.

Zhang *et al.* [41] use BLE RSSI fingerprint for indoor localization. In the offline phase the Motiosens UWB sensors together with the BLE beacons are used to construct the fingerprints. The testing environment is a room equipped with 12 BLE beacons and 8 UWB anchors. The beacons send advertisement packets every 350 ms with -4 dBm transmit power. All anchors (BLE and UWB) are 1.5 m from the floor. The data is collected from the BLE scanner and the UWB tag every second and uploaded in the location server. The UWB localization accuracy is tested with a tag located on the tripod (perfect LOS) and a person carrying a tag. Authors describe the latter as real conditions, but no other obstacle is put in the open space. The mean error for the tripod configuration is 0.039 m. When a person is carrying the tag the mean error is less than 0.521 m. To estimate the location through fingerprints authors use Machine Learning algorithms: k-Nearest Neighbor (KNN) and Gradient Boosting Decision Tree (GBDT). The system is trained with 80 % of the fingerprints collected. Authors validate the accuracy of the system on the remaining 20 %. The results show the mean distance error for different algorithms: Basic geometry - 2.83 m, KNN - 0.72 m, GDBD - 1.27 m, Random Forest - 0.85 m.

Khan *et al.* [100] evaluate the use of Machine Learning techniques and signal processing in order to improve the performance of Bluetooth AoA estimation. Authors propose a method of combining MUSIC algorithm with regression models including Gaussian Process (GP), Neural Network (NN), and Regression Tree (RT) in order to perform AoA estimation. For the machine learning model authors used 75 % of the data to train the model and 25 % for test the system. Authors are evaluating the proposed approach with simulations and real measurements, where the authors don't mention which commercial devices they use for real AoA measurements. The simulation results show that for 30 dB SNR when the multi-path effects and elevation angle are low the

azimuth estimation was 20 % better for NN than the baseline MUSIC algorithm and 50 % better in case of RT and GS. For the SNR of 30 dB and with elevation increasing the NN and the GS outperforms the baseline MUSIC. For this case the RT had comparable results to the MUSIC algorithm. In the case of SNR between 0 dB and 30 dB the estimation improved for both the NN and the GP approach. The real measurements give the Mean Absolute Error in AoA estimation as follows: MUSIC - more than 9°, NN 3.5°, GP 3°, RT 3.5°. Measurements are done with an elevation angle from 0° to -20°. Authors state that the GP approach gives the best results but has the computational time of 40 ms. This is a lot slower compared to NN's 7.8 ms to process a single test set of 1530 samples. The RT approach has the fastest computational time of 1.4 ms but its performance degrades with higher elevation angle and lower SNR.

Hajiakhondi *et al.* [101] describe the signal processing methods to minimize the error of AoA estimation in BLE. Proposed processing framework is done in three steps. First, Nonlinear Least Squares (NLS) curve fitting is proposed for reducing the noise after the I/Q signals are collected and is applied to raw data. All data is fitted in sinusoidal curve. Second, authors use Kalman Filter (KF) for smoothing the phase and frequency variations on different samples. These variations cause big errors when estimating the angle and happen due to the phase shift of oscillator in both the transmitter and the receiver sides as well as in the switching elements. Third, Gaussian Filter (GF) is implemented for eliminating Wi-Fi interference on the BLE channels causing angle calculation error. A constant angle offset is calculated for all 37 BLE data channels in order to improve the angle estimation. Authors use Texas Instruments RTLS development kit with BOOSTXL-AOA antenna array for the experimental evaluation. The AoA is estimated in the area from -90° to 90°. After processing the raw data the results show that from -60° to 60° this method gives the errors of less than 10°. Errors grow significantly when moving towards -90° and 90° and the AoA estimation are almost random.

Jondhale *et al.* [102] present the indoor tracking solution based on Generalized Regression Neural Network (GRNN). Authors further use Kalman Filter (KF) and The Unscented Kalman Filter (UKF) in order to improve localization accuracy. For evaluation their approach authors utilize off the shelf BLE devices as anchors which send beacons to a smartphone that tracking person carry. Collected RSSI are then transferred to a central computer which computes the calculation of 2D position using proposed algorithms. Authors compare traditional trilateration method with GRNN, as well as trilateration + KF/UKF and GRNN + KF/UKF. The testing site is a lab area 10 m x 15 m equipped with four anchors (Cypress CYBLE-022001-00 BLE nodes) and smartphone (Motorola G4 Plus). Authors train proposed tracking system with the set of 70 RSSI samples and validate their approach with 35 RSSI samples. The accuracy of the system is evaluated using average localization error and RMSE. In the first phase of the research evaluation authors compare traditional trilateration to GRNN approach. Authors report the Average RMSE below 1 m in case of GRNN algorithm. The Average Localization Error and the Average RMSE is reduced by 59 % and 48 % with the GRNN approach compared to trilateration. In the second phase of evaluation authors compare trilateration + KF/UKF and GRNN + KF/UKF. Authors report that the fusion of

GRNN and KF approach can provide very high tracking accuracy of centimeter scale. The Average Localization Error and the Average RMSE is lowest for the GRNN + UKF algorithm and is 6 cm and 8 cm, respectively.

Jondhale *et al.* [103] evaluate the use of Support Vector Regression (SVR) in RSSI-based indoor positioning systems. Authors compare the proposed SVR scheme to traditional trilateration and GRNN. Furthermore, authors fuse SVR scheme with KF in order to improve the accuracy. For evaluating their approach authors use simulations, where they track a mobile device using six anchor nodes deployed in a 100 m x 100 m. The proposed SVR localization model was trained with 120 input vectors, each containing three RSSI measurements from three anchors and 120 corresponding 2D positions of the mobile target. Authors use Log-Normal Shadowing Model (LNSM) to generate RSSI values and perform simulations in two phases. In phase I, SVR localization is compared to traditional trilateration and GRNN. Comparing to trilateration results simulations show an average RMSE decreased by 52 % and 62 % and average localization error decreased by 51 % and 66 % using GRNN and SVR respectively, In phase II authors compare SVR method to SVR fused with KF. The average RMSE and average localization error with the SVR + KF scheme decreased by approximately 95 % and 79 %, with average RMSE of 26 cm and average localization error of 85 cm for 2D localization.

Horvath *et al.* [104] present the Ultra-Wideband (UWB) Two Way Ranging (TWR) algorithm that uses the passive approach in two way ranging together with double-sided exchange of messages between anchors and tags. This method could be suitable for applications where extended battery life. In passive TWR, if anchor 2, which does not take part in the process of two-way ranging between the anchor 1 and the tag, can receive their messages then the distance between anchor 2 and the tag can be determined as well. This way the number of ranging messages can be reduced to only two messages instead of communicating with all anchors one by one. The authors present a mathematical analysis of the ranging error propagation of the TWR, Passive TWR, Extended TWR and Passive Extended TWR. Passive TWR is explained as a good solution to avoid message exchange with every anchor and it is a good way to extend battery life. Passive Extended TWR improves the accuracy and together with the message number reduction allows for a smaller energy consumption. The proposed method is therefore a good candidate for battery constrained ranging applications. However, this paper doesn't present a simulation or implementation of the proposed Passive Extended TWR.

Bonafini *et al.* [105] present the solution for positioning in order of tenth of a meter and time synchronization in order of milliseconds using the UWB Decawave DWM1001 modules. Authors are exploiting UWB short pulses and accurate ToA estimation to create time synchronization for the end nodes. The experiment is performed using DWM1001-DEV boards with DRTL5 software provided by Decawave. With this software UWB anchors and tags form a network where they communicate by TDMA as a MAC layer. Here the superframe carries all the information about anchors and performed ranging. The ranging algorithm used in this paper is SDS-TWR. Authors want to exploit the RX_SFD signal that is generated at the reception of the beacon sent by the network coordinator anchor (BCN0), record the time when the microcontroller detected

this signal and compare its internal clock drift to the network coordinator as a reference time. Presented results show the time reference from UWB nodes of a DRTLS network with a maximum jitter of 3.3 μs and a standard deviation of 0.7 μs .

Kolakowski *et al.* [106] present cooperative localization using TDoA and TWR fused together through EKF. In the presented approach the tags transmit the UWB packet to the anchors for TDoA calculation and are also capable of performing TWR with other tags. Tags send TWR results to the anchors over the UWB interface. Anchors measure time of packet arrivals and transmit all gathered results to the system controller. The proposed approach was tested in Matlab simulation and experimentally. The algorithms precision was simulated by comparing the Circular Error Probability (CEP) for TDoA and the cooperative method. CEP is calculated for 68 % of the derived results. Comparing to just TDoA, the use of cooperative algorithm improved the quality of the calculated tag positions using the CEP metric. Authors report the highest CEP value for combining TDoA and TWR system is close to 45 cm. In the experimental evaluation authors use a TDoA-based positioning system with 6 anchors and 1 reference anchor, and the EVK1000 evaluation kit for TWR measurements. The reference anchor in TDoA positioning system is equipped with TCXO used as a reference clock for synchronization. Similar to the simulation, when looking at the CEP metric for 68 % of the measurements taken, results show that the positioning precision has been strongly improved with cooperative approach compared to just TDoA. However, the use of cooperative algorithm did not improve positioning accuracy which was worse than by just using TDoA positioning system alone. Authors claim that such effect can be prevented by employing an algorithm for selecting the best set of nodes to range with.

Pannuto *et al.* [107] present a new design of UWB tags and anchors for providing decimeter level accuracy. The proposed solution implements the bandstitching technique for signal reconstruction at the receiver's side instead of using fast ADC and real time sampling. The developed solution is evaluated in the use case of tracking a micro quadrotor, with a surface area of 250 m^2 . Authors use TDoA technique, where the anchors are synchronized between each other, and tag transmits UWB pulse continuously. Authors have designed custom tags and anchors from available commercial electronic parts. They give a detailed description of how the tag and anchor are designed and built. The tag is made of a 3.9 x 1.5 cm PCB with a 2.4 x 2.2 cm UWB antenna. The entire tag fits within a 3.9 x 2.2 x 0.2 cm bounding box or about 1.5 cm^3 . The tag weighs 3 g and draws 75 mW of power. The anchors consist of a central 6.7 x 5.8 cm PCB with three 2.4 x 2.2 cm UWB antennas mounted co-planar at 120° offsets to avoid cross polarization. Each anchor needs a dedicated USRP1 for signal processing and data transport to a computer, where one USRP1 can service up to two anchors. The use of commercial off the shelf SDRs add significantly to the cost of the anchors. Authors report that one 3.2 GHz Xeon core can solve a position estimate in 231 ms and that at least five parallel cores are required to maintain a 19 Hz update rate. Harmonium achieves a median of 14 cm error with a 90th-percentile error of 31 cm and median precision of 9 cm, having motion capture as a ground truth with millimeter precision. Authors mention that they didn't compare this system to the Decawave UWB solution.

Chantaweesomboon *et al.* [108] present the hands-on evaluation of the TREK1000 RTLS kit provided by Decawave. Multiple scenarios were evaluated with configurations using three and four anchors. RTLS algorithm uses the trilateration method and TWR is the technique applied between tag and anchors. TREK1000 allows for a change in RF settings and the use of 4 different modes: L2 - channel 2 with 110 kbps data rate, L5 - channel 5 with 110 kbps data rate, S2 - channel 2 with 6.8 Mbps data rate and L5 - channel 5 with 6.8 Mbps data rate. Slow position update rate was reported when using the long frame L2 and L5 modes. Indoor performance evaluation for 2D localization show around 50 % of the data reporting 50 cm error or less, with no impact on accuracy having the 4th anchor included for 2D localization. For 3D localization in the indoor scenario results show worse performance with 3 m error for 50 % of samples, also with no significant difference between 3 or 4 anchors. Outdoor 2D localization error was sub 70 cm for 100 % samples, sub 10 cm for around 50 % of the measurement samples. Authors report that the S2 mode provided the estimated locations with the smallest distance error. As for the indoor environment, there was no significant difference when using the additional fourth anchor for 2D outdoor localization. In the outdoor setup three out of four anchors were placed at height of 130 cm and the fourth anchor was placed at height of 100 cm. 3D outdoor localization performance is evaluated with tag set on two different heights, 110 cm and 150 cm. Authors report less than 3 m of error on 100 % measurement samples in the case where the tag is at 110 cm height, located between two planes covered by the anchors. When the tag is positioned at 150 cm (above all anchors) position estimation is worse with less than 4 m error on 100 % of the measurement samples. The authors point that the anchors should be in the boundaries of the localization area. Also, at least two pairs of anchors should be in LoS and located 2-3 m above the ground. Finally, authors conclude that not all anchors should be in the same plane, with one anchor located far from the plane of first three anchors in order to have better z axis estimation.

Kulmer *et al.* [109] present the work on UWB localization using a single anchor. Authors exploit the possibility of using multi-path propagation together with LOS signal to determine the tag's position. For this approach previous knowledge of the environment is needed to determine the strong multi-path components reflections. The evaluation of the proposed approach is done using the Pozyx off the shelf devices which include the DW1000 transceiver ICs. To estimate the tag's position authors exploit the possibility of the position related information located in the Channel Impulse Response (CIR) measurements. The DW1000 IC is capable of returning the CIR value which makes it suitable for evaluating this approach. Position estimation is done at 100 different positions within 27 x 27 cm grid, where the moving tag is placed. Results show that with strong reflected signals with big Signal-to-Interference-plus-Noise-Ratio (SINR) the position error of both channels is decreased and the 90 % limit of the CDF is reached within approximately 0.5 m of positioning error.

Barua *et al.* [110] give the evaluation of the UWB TWR distance measurements in an underground mine. The authors use TREK1000 evaluation kit from Decawave. Two scenarios are examined, LOS and NLOS, with distance between nodes up to 15m. In the NLOS scenario the first two meters were LOS due to the testing site "L shape"

configuration. The measurements were performed using 4 different settings on two channels: L2 - channel 2 (4 GHz) with 110 kbps data rate, L5 - channel 5 (6.5 GHz) with 110 kbps data rate, S2 - channel 2 (4 GHz) with 6.8 Mbps data rate and L5 - channel 5 (6.5 GHz) with 6.8 Mbps data rate. In the LOS scenario the minimum RMSE of 20-30 cm has been observed for the L2 setting. The maximum RMSE for LoS up to 1 m for S5 setting. For the NLOS scenario the minimum RMSE of around 1.5 m has been reported for the L5 setting. Maximum RMSE for NLoS of up to 2 m is measured for the S2 operational mode.

Zhao *et al.* [111] propose a framework for improving UWB TDoA localization accuracy for recourse constrained mobile robots. The proposed framework tackles two challenges: the systematic bias caused by antenna radiation characteristics and outliers caused by NLoS and multi-path. The systematic bias is compensated with lightweight NN and outliers are handled with M-estimation based EKF. Authors partitioned the dataset into training, validation and testing using a 70/15/15 split. The proposed approach allows the real-time execution and is validated on-board a Crazyflie 2.0 nano-quadcopter. In this paper the quadcopter is equipped with IMU and UWB tag based on DW1000 IC. Test setup also include 8 UWB TDoA anchors and a motion capture system as a ground truth, installed a 7 m x 8 m x 3 m room. In this test setup M-estimation EKF-only is used as a baseline and is compared against the estimation enhanced NN, with and without the anchor orientation information. Authors report that proposed approach with NN bias compensation, considering the anchor orientation gives the best results. Results show an average of 42.09 % localization error reduction compared to the baseline, with approximately 0.14 m RMS localization error on-board a Crazyflie.

We present our classification criteria and recent academic papers on indoor localization in Table 2.1. We selected the thresholds for our classification to match our DotBot localization use case, introduced in Section 2.1. First criteria in the table is the *LoS requirement*, i.e. if the localization system needs LoS to work. Then, we introduce *accuracy*, where we consider a < 10 cm accuracy as a precise localization. *Update rate* of the localization of at least 10 Hz is needed to match our use case. As low-power localization systems we consider those where the mobile device has > 1 year of *battery life*. According to our DotBot use case we consider a mobile device with the *cost* of $< \text{USD } 20$ to be low-cost.

2.3.4 Discussions

From the research conducted by the various authors in the light-based, sound-based and RF-based localization technologies we highlight the following.

- Light-based localization solutions usually provide centimeter level accuracy. The work done with IR lighthouse technology shows promising results in terms of accuracy, battery life and cost. In order to implement this solution, the necessary hardware requirement for a mobile device is the optical receiver module. On the other hand, the anchors are off the shelf devices that don't need any additional development. However, depending on the application requirements this technology

Table 2.1: Classification of the recent academic research papers on indoor localization.

research paper	arch. approach	technique	technology	LoS	accuracy	upd. rate	bat. life	cost
Aswin <i>et al.</i> [86]	outside/in	RSS	visible light	yes	> 10 cm	?	?	< USD 20
Kilberg <i>et al.</i> [87]	outside/in	AoA	IR lighthouse	yes	> 10 cm	?	< 1 year	< USD 20
Kilberg <i>et al.</i> [88]	inside/out	AoA	IR lighthouse	yes	< 10 cm	?	> 1 year	< USD 20
Campos <i>et al.</i> [22]	inside/out	AoA	IR lighthouse	yes	< 10 cm	> 10 Hz	?	< USD 20
Yan <i>et al.</i> [90]	inside/out	AoA	IR	yes	< 10 cm	> 10 Hz	?	?
Qi <i>et al.</i> [91]	outside/in	ToF	ultrasound	yes	< 10 cm	?	< 1 year	> USD 20
Esslinger <i>et al.</i> [92]	outside/in	ToF	ultrasound	yes	< 10 cm	?	< 1 year	?
Rekhi <i>et al.</i> [93]	outside/in	ToF	RF/acoustic	yes	< 10 cm	?	> 1 year	< USD 20
Nandakumar <i>et al.</i> [94]	outside/in	PoA	backscatter	no	< 10 cm	?	> 1 year	< USD 20
Ahmad <i>et al.</i> [95]	outside/in	PoA	backscatter	yes	< 10 cm	?	> 1 year	< USD 20
Yang <i>et al.</i> [40]	outside/in	ToF/AoA	Wi-Fi	no	> 10 cm	?	< 1 year	< USD 20
Yu <i>et al.</i> [96]	outside/in	ToF/RSS	Wi-Fi	no	> 10 cm	< 10 Hz	< 1 year	< USD 20
Alletto <i>et al.</i> [97]	outside/in	RSS	Bluetooth	no	> 10 cm	?	< 1 year	> USD 20
Faragher <i>et al.</i> [98]	inside/out	RSS/Fingerprint	Bluetooth	no	> 10 cm	> 10 Hz	< 1 year	< USD 20
Zhang <i>et al.</i> [41]	outside/in	RSS/Fingerprint	Bluetooth	no	> 10 cm	?	?	?
Khan <i>et al.</i> [100]	outside/in	AoA	Bluetooth	yes	?	?	?	?
Hajiakhondi <i>et al.</i> [101]	outside/in	AoA	Bluetooth	yes	?	?	?	> USD 20
Jondhale <i>et al.</i> [102]	outside/in	RSS/GRNN	Bluetooth	no	< 10 cm	?	?	< USD 20
Jondhale <i>et al.</i> [103]	outside/in	RSS/SVR	?	no	> 10 cm	?	?	?
Horvath <i>et al.</i> [104]	?	ToF	UWB	no	?	?	?	?
Bonafini <i>et al.</i> [105]	outside/in	ToF	UWB	no	?	?	< 1 year	< USD 20
Kolakowski <i>et al.</i> [106]	outside/in	TDoA/ToF	UWB	no	> 10 cm	?	< 1 year	> USD 20
Pannuto <i>et al.</i> [107]	outside/in	TDoA	UWB	no	> 10 cm	> 10 Hz	< 1 year	< USD 20
Chantaweesomboon <i>et al.</i> [108]	outside/in	ToF	UWB	no	> 10 cm	> 10 Hz	< 1 year	> USD 20
Kulmer <i>et al.</i> [109]	outside/in	ToF	UWB	yes	> 10 cm	?	?	> USD 20
Barua <i>et al.</i> [110]	outside/in	ToF	UWB	no	> 10 cm	?	?	> USD 20
Zhao <i>et al.</i> [111]	inside/out	TDoA	UWB	yes	> 10 cm	> 10 Hz	< 1 year	< USD 20

may not be suited for outdoor localization systems or those covering large areas. The main constraints of light-based technologies are limited range (5 m in case of IR lighthouse), LoS requirement and poor performance for outdoor use.

- Sound-based localization solutions are able to provide the necessary accuracy for centimeter level localization. These systems can provide bigger range than IR lighthouse. However, extending the range is power demanding and is not suited if the mobile device needs to operate for many years on batteries. Some sound-based localization systems can benefit from the ubiquity of the acoustic infrastructure in smartphones. In the case of ultrasound, we need additional hardware such as ultrasound transducers, the circuits for transmitting and receiving the ultrasonic pulse. There are some of the shelf sensors that could be considered. They are usually stand-alone devices designed to measure distance between the sensor and an obstacle. We need to develop additional hardware in order to allow these devices to measure distances between one another. Moreover, researchers need to develop solution for time synchronization between the sensors. Finally, the main constraints of these technologies are LoS requirement, higher battery consumption and unstable accuracy in different environment conditions.
- RF-based technologies are the most frequently used in indoor localization research in recent years. The work by authors covers many different RF technologies such as: Bluetooth, Wi-Fi and UWB. Due to their poorer accuracy compared to light- and sound-based solutions, researchers use different techniques and filtering algorithms to improve the performance. The increasing market demands for indoor localization systems motivated many semiconductor companies to invest in making SoC able to provide localization capabilities. Unlike the light and sound, RF is not constrained with LoS requirement and can work in NLoS conditions. These solutions can work indoor as well as outdoor if the system uses appropriate localization technique and filtering. Selecting the appropriate RF technology can satisfy low-power and low-cost requirements. As previously mentioned the main constraint of these solutions is their limited accuracy if we use off the shelf products. Researchers need to employ different techniques and algorithms in order to improve the accuracy performance of the RF-based system.

In an outside/in architecture approach, a centralized system runs the computationally demanding algorithms. Researchers employ schemes such as machine learning and filtering algorithms to improve the accuracy of the system. Authors report that schemes such as Neural Networks (NN) and Regression Trees (RT), used to improve AoA estimation, have a computational time of maximum 7 ms [100]. In case of RSSI-based estimations using schemes like GRNN and SVR combined with KF researchers report 4 ms computational time [103]. Most personal computers today are able to provide necessary computational power for indoor localization systems with outside/in approach.

For the distributed systems with inside/out architecture approach, we need to select the appropriate scheme carefully in order to implement the algorithm on today's low-power and low-cost SoCs. State of the art SoCs like nRF52833 provide low-power

capabilities with powerful 64 MHz Arm Cortex-M4 [112]. We can easily implement techniques such as triangulation and trilateration, as well as sensor fusion on such devices. Some commercial solutions use Arm Cortex-M4 microcontrollers to implement filtering algorithms such as KF and EKF, in order to fuse data from inertial measurement units and GPS [113]. Using similar design architectures in the inside/out approach researchers can implement computationally demanding algorithms in order to improve the accuracy performance of their systems.

2.4 Open Research Challenges

While many researchers are trying to raise the bar and improve the existing localization solutions there are still many open research challenges. From the academic research surveyed in Section 2.3, we identify the five main research challenges in indoor localization that are yet to be solved in order to improve existing localization solutions: zero infrastructure dependency (Section 2.4.1), lightweight filtering algorithms (Section 2.4.2), low-power operation (Section 2.4.3), security (Section 2.4.4), standardization (Section 2.4.5).

2.4.1 Zero Infrastructure Dependency

In most cases, indoor localization systems rely on existing infrastructure. They usually use existing Ethernet or Wi-Fi local area networks to communicate. Also, most localization solutions provide just the localization capability and cannot handle additional data exchange between devices inside the system. Allowing devices to transfer sensor readings and actuator commands together with localization data has a huge commercial potential. When designing a zero-infrastructure system, we also need to examine the mains power constraint. In most cases, localization systems are constrained by AC power supply requirements. Mains power is used to provide electricity to the localization infrastructure or “anchors” in the localization system. Overcoming networking and mains power constraints would lower installation costs and it is essential when designing a localization system in constrained environments.

2.4.2 Lightweight Filtering Algorithms

In RF-based localization, multi-path effects and noise create big outliers in location estimation and cause low localization accuracy. This is due to the very nature of the radio signals. Transmitted radio signals can be reflected as they bounce from obstacles like walls, objects or humans. Thus, many copies of the same signal arrive at the receiver with a certain time delay. For most localization techniques, it is essential to estimate the shortest path of the signal from transmitter to receiver. This is not a trivial task and a lot of research has been conducted to solve this challenge. Typically, complex signal processing techniques and filtering algorithms are used to improve the accuracy and identify the shortest path of the signal. These techniques are usually too “heavy” for the resource constrained mobile devices, especially in distributed systems. Hence,

there is a need for developing lightweight and efficient signal processing and filtering algorithms to mitigate multi-path effects and noise in order to obtain the shortest path of the signal. These algorithms allow mobile devices with limited processing power to obtain high accuracy, while maintaining low-power operation.

2.4.3 Low-Power Operation

Depending on the application requirements, many use cases require a battery powered mobile device. In some cases, mobile device can have a rechargeable battery and the user needs to recharge it after a certain period of time. Yet, some applications require a battery-powered device with years of battery life, like our DotBot use case introduced in Section 2.1. Moreover, allowing a mobile device to be tracked without frequent changing of its battery improves user experience and reduces human labor and costs. There are many localization solutions providing years of battery life on the tag i.e. mobile device. However, battery-powered localization infrastructure with years of battery life is rarely examined. Some sound-based solutions provide battery powered infrastructure, but the battery needs to be recharged at least once every month. There are some commercially available industrial WSN, offering more than 10 years of battery life and these technologies should be considered when designing ultra low-power localization systems [114], [115]. Designing a localization system with multiple years of battery life for both mobile devices and anchors would open many different applications and presents a big commercial opportunity.

2.4.4 Security

The security of localization systems and data privacy presents a significant open challenge for most applications. In industrial applications, the security issues in the localization system could cause irreparable damage to the production process or safety issues endangering people at their work site. In other applications like contact tracing in the health emergency crisis like a COVID-19 pandemic, users are not easily convinced to provide the permission for proximity detection, due to the possible privacy issues. Additionally, the limited computational power on some recourse and energy constrained devices deployed in localization systems cannot handle complex security approaches. Therefore, there is a need for developing energy efficient and computationally undemanding security system.

2.4.5 Standardization

Unlike the GPS which is adopted as a global standard for outdoor localization and navigation, indoor localization doesn't have its main single technology. This means that no matter how well we design our localization system once we leave the area of the deployment it is most likely that our mobile device won't work with other localization systems on different deployment sites. This is a big disadvantage and presents the

opportunity for creating a universal standard which will be adopted by different devices across different applications.

2.5 Summary

The aim of this chapter is to survey the recent research related to the topic of this thesis, and to identify main research challenges for constrained localization systems. By having the guiding use case, the localization of miniature wireless robots, we are able to present specific application requirements for the low-cost and low-power localization system. This allows us to focus our research and survey recent academic work on indoor localization that could satisfy these requirements. We give a detailed description of the work presented in the papers and provide a classification according to the five criteria: Line-of Sight (LoS) requirement, accuracy, update rate, battery life, cost. Finally, we identify five main open research challenges: lightweight filtering algorithms, zero infrastructure dependency, low-power operation, security, standardization. We believe that overcoming these challenges is crucial in order to make indoor localization ubiquitous and enabled on all devices in the world of IoT.

Chapter 3

Methodology

Key Takeaways: This chapter presents the methodology used to develop and evaluate proposed solutions in this thesis. We explain why the hands-on approach is challenging and complementary to analysis and simulation in low-power wireless systems. We present the experimental setup for each of the main contribution chapters of this thesis. We give a detailed description of the existing IoT network and devices in the Sète marina, that are used to develop WELOC (Chapter 5) and Blip (Chapter 6). Finally, we show the experimental setup for RRDV (Chapter 7).

3.1 Introduction

Experimental evaluation and development of real-world systems are crucial in low-power wireless, and play a significant role in the research presented in this thesis. One of the primary reasons why experimental evaluation is necessary in the low-power wireless research field is the complexity of real-world environments. Such systems often operate in environments with numerous factors that can affect their performance, such as the presence of obstacles, interference from other wireless devices, and changes in environmental conditions. These factors are challenging to simulate accurately, and hands-on experiments provide a more accurate representation of the system's performance in real-world conditions. Additionally, an applied approach is needed because of the hardware limitations of low-cost, low-power hardware platforms that can affect the performance of the system. This can make it difficult to accurately simulate the system's behavior. Experimental evaluation allows one to evaluate the system's performance under real-world hardware constraints. Finally, experimental evaluation is essential for prototyping and testing of the low-power wireless systems before deployment, allowing researchers to identify and address any issues before deployment, leading to more reliable and effective systems. In this research, experimental evaluation and real-world testing were used extensively to evaluate and optimize the performance of proposed systems. The solutions we propose are tested in a real-world environment in order to

evaluate their performance under realistic conditions. For each solution we design a proof-of-concept (POC) system, which led to two patent applications being filed during this thesis.

The primary goal of our work is to develop a reliable and accurate localization system for a smart marina environment. We analyze the existing literature (Chapter 2) and find that most of the previous work uses analysis and simulations, or in-laboratory experimentation. Analysis and simulation are important, and can be complemented by experimentation. The topic of this research belongs to low-power wireless systems, which are unreliable in their nature and hard to simulate. To overcome this limitation, we develop a real-world solution that takes into account the unique challenges of our driving use cases, presented in Section 1.6. We use the existing IoT network, already present in the marina, to build the localization system presented in Chapter 5, which is based on the combination of RF and ultrasound technology. Additionally, we utilize the real-world datasets, generated by the IoT devices deployed in the same marina, to develop accurate and reliable boat identification solution (Chapter 6), further validating our approach. Finally, we propose a solution for mobile robot encounter detection in a swarm, and test experimentally building a five mobile robot demonstrator (Chapter 7).

The methodology of my thesis consists of several steps. *First*, we test popular commercial RTLS solutions for AoA estimation and UWB ranging to gain the knowledge in the field. *Second*, we design and implement the ultrasound-based localization system, which is based on a combination of time-synchronization over the radio and ToF measurements. We conduct a series of experiments in the marina in the South of France to collect real-world data, which we used to validate the approach. *Third*, we design and evaluate the performance of our boat identification solution, using real-world datasets, collected in the same marina environment. We compare the results of our algorithm with ground truth data to assess its accuracy and reliability. *Forth*, after designing the localization system for the marina environment, we apply the know-how to our second driving use case, mobile robots. We propose a system that is able to detect encounters between robot pairs in a swarm, which is an important problem in multi-robot systems. We utilized radio and ultrasound technology to measure the distance between robots and detect encounters.

This chapter is organized as follows. Section 3.2 provides a detailed description of the experimental setup and tools used in this thesis. Section 3.3 concludes this chapter.

3.2 Experimental Setup

In this section we describes the experimental setup, evaluation kits and tools used for this research. Section 3.2.1 shows the commercial evaluation kits used for evaluating popular AoA and UWB solutions, presented in Chapter 4. Section 3.2.2 describes the Sète marina in the South of France and Falco IoT network of devices installed inside the marina, used in solutions proposed in Chapters 5 and 6. Section 3.2.3 presents the hardware and experimental setup used for evaluating robot encounter detection solution proposed in Chapter 7.

3.2.1 Angle of Arrival and Ultra-Wideband Commercial Solutions

We want to evaluate turnkey Real-Time Localization Systems (RTLS) solutions on the market, which offer a fast and easy to install apparatus for evaluation. After surveying the market for Angle of Arrival (AoA) and Ultra-Wideband (UWB) devices we select the following development kits for testing:

- Texas Instruments AoA,
- Nordic Semiconductor AoA,
- Decawave UWB.

Texas Instruments is one of the few semiconductor companies on the market that offers a commercial development kit together with an antenna array for evaluating AoA direction finding. The AoA development kit comprises the BOOSTXL-AOA kit and CC26X2R LaunchPad evaluation boards. The former consists of two orthogonal antenna arrays with three dipole antennas operating at 2.4 GHz (Fig. 3.1). Firmware and direction viewer software are also provided by Texas Instruments as a part of SimpleLink CC13X2-26X2 SDK 4.30. The evaluation kit from Texas Instruments provides raw angle estimation without any filtering algorithm by default, which leaves the RTLS designer to choose the appropriate algorithm to improve performance when designing a localization system.

Nordic Semiconductor offers multiple SoC development boards with enabled Bluetooth direction finding. One of them is the nRF52833-DK board which has low-power multiprotocol SoC with a wide operating temperature range. In cooperation with Nordic Semiconductor, we received the AoA development kit with two nRF52833-DK boards and antenna array for testing its AoA estimation capabilities. The antenna array has 12 patch antennas located on a square shape PCB in a plane configuration capable of estimating both azimuth and elevation angle (Fig. 3.2). Necessary firmware and direction viewer software was also provided by Nordic. Unlike the Texas Instruments software, Nordic's direction viewer software has the ability of showing real-time filtered data which significantly improves the result. Unfortunately, there is no explicit information on which filtering algorithm the software is using. It is also possible to obtain unfiltered angle estimations, but in order to highlight the importance of filtering the raw measurements in this experiment we collect filtered measurements.

Decawave is one of the companies that pioneered the commercialization of the UWB ranging solutions, and is currently the market leader. Therefore, solutions provided by the Decawave were the obvious choice for evaluating UWB TWR. For this purpose, we use DWM1001-DEV development boards from Decawave, which feature the DWM1001 UWB module. This development board has the external GPIOs, state LEDs, on-board USB connection and J-LINK which simplify firmware development. The DWM1001 module is composed of an IEEE 802.15.4-2011 UWB compliant transceiver DW1000, a Nordic Semiconductor nRF52832, a 3-axis motion detector, an UWB and BLE antennas.

We evaluate AoA solutions in an indoor scenario, in a 50 m² apartment. The testing site and the configuration of the AoA estimation experiment, with Texas Instruments

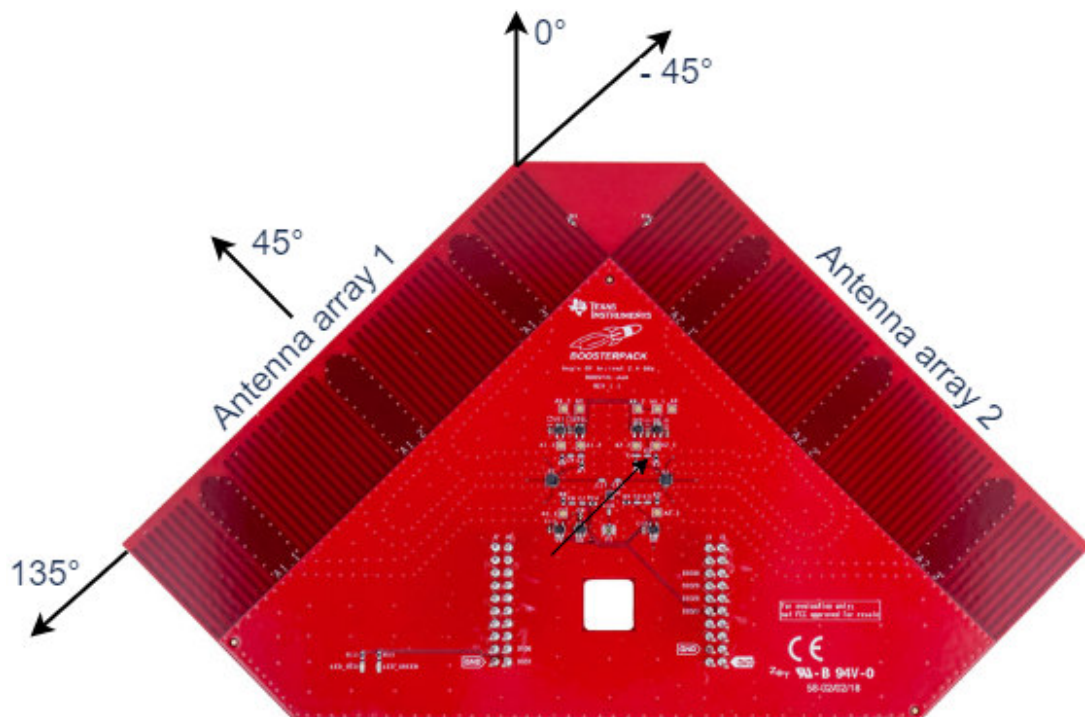


Figure 3.1: BOOSTXL-AOA antenna array from Texas Instruments.

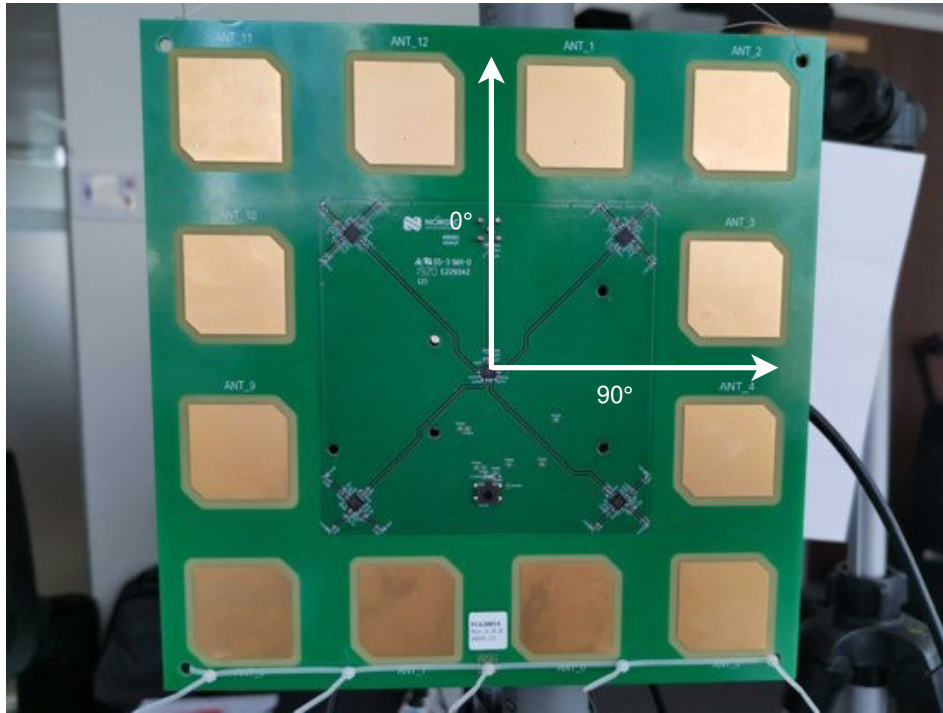


Figure 3.2: Antenna array provided by Nordic Semiconductor.

and Nordic evaluation kits, is shown Fig. 3.4. We evaluate the accuracy and the range of the UWB modules in an outdoor environment. Fig. 3.5 shows the map of the outdoor site, with each measurement point depicted with markers.

3.2.2 Sète Marina

In order to develop and evaluate localization system for smart marina, proposed in this thesis, we use the Sète marina in the South of France. This marina is outfitted with a commercial-grade IoT network, designed and supplied by Falco. Falco develops different types of low-power wireless sensors for real-time monitoring of boats, their presence at slips and respective current consumption. Once deployed, the sensors form a wireless mesh network around a central gateway. They communicate over a 2.4 GHz radio, using a protocol similar to 6TiSCH [116]. Data from the sensors is transferred over the Internet to the cloud application. Fig. 3.6 shows the Sète marina in the South of France, which is entirely equipped with the Falco Presence devices, installed on each of its 471 slips.

In order to design systems proposed in Chapters 5 and 6, we use commercial IoT sensors: **Falco Presence** and **Falco Boat**. For enabling WELOC localization system, we use the fixed infrastructure of Falco Presence devices. For designing Blip to identify boats, we combine data from the Falco Presence and Falco Boat devices (Fig. 3.7). Apart from their primary functions to send, in real-time, the slip occupancy and boat parameters, we use additional data that these devices generate as our real-world dataset



Figure 3.3: Decawave DWM1001-DEV.

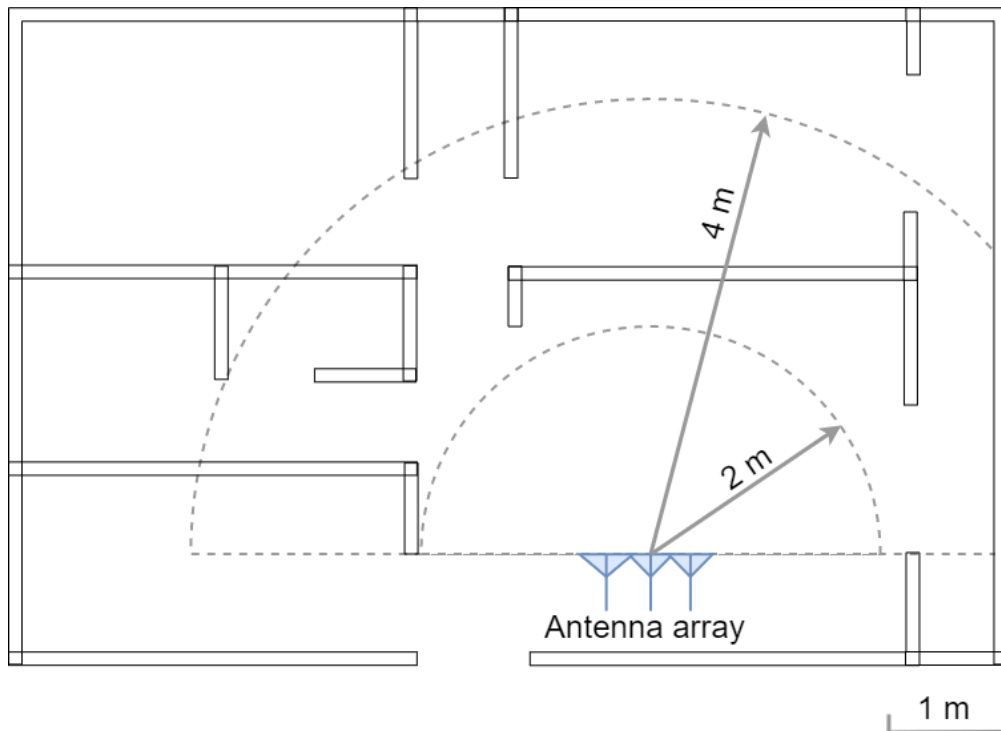


Figure 3.4: AoA estimation testing site.

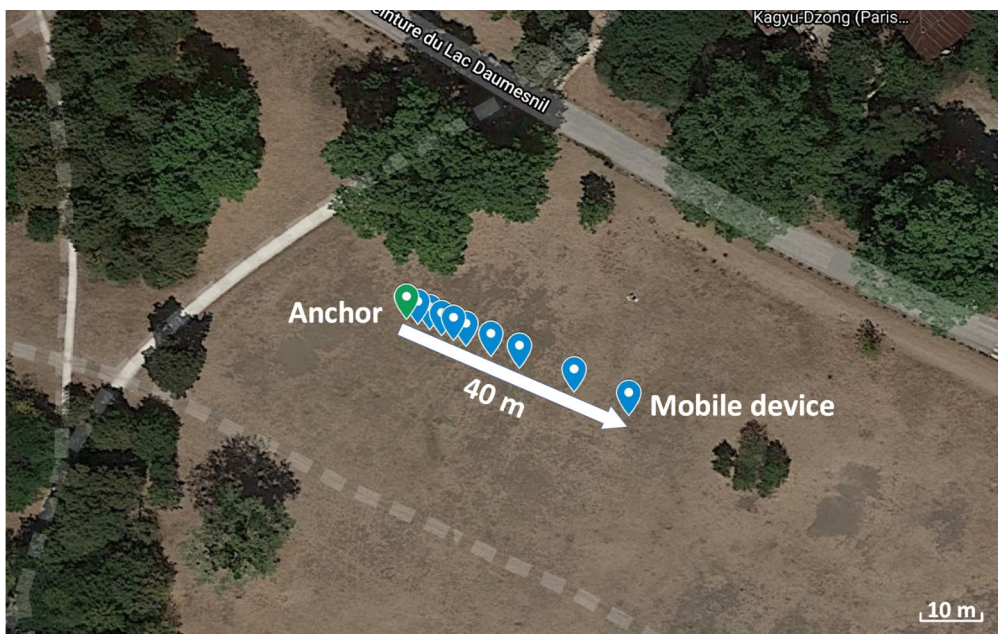


Figure 3.5: UWB ranging testing site.

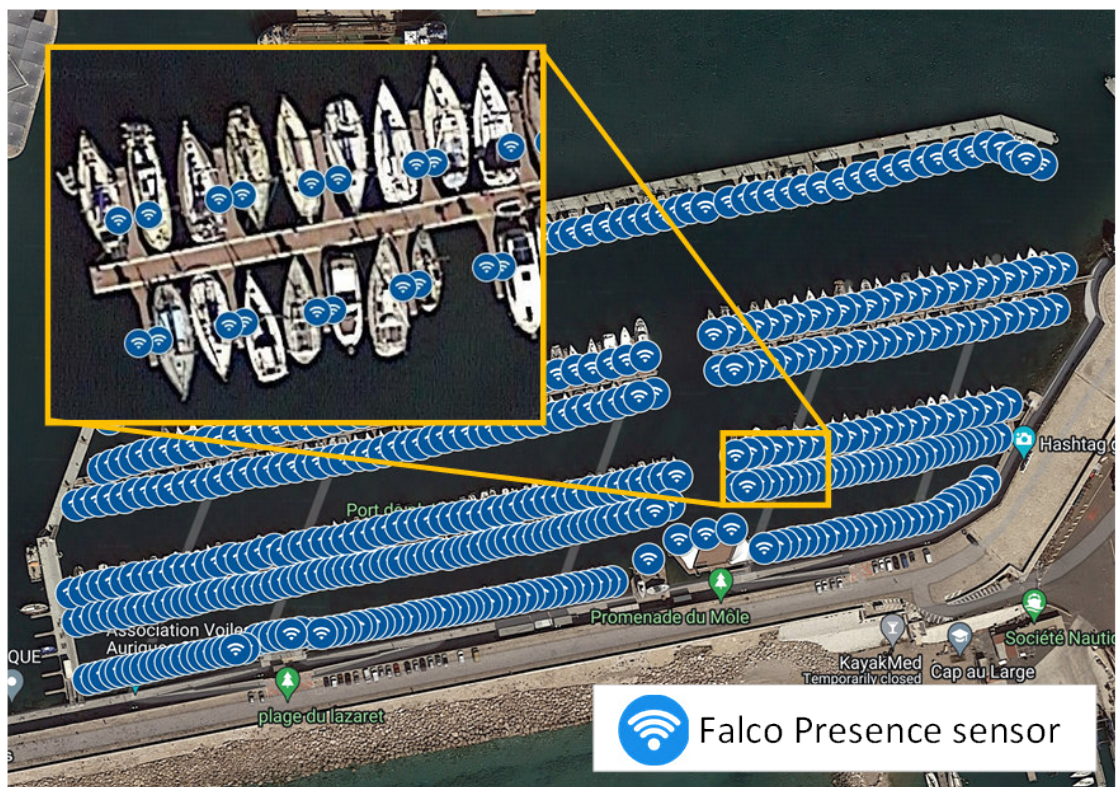


Figure 3.6: Falco Presence sensor infrastructure in the Sète marina in the South of France. Each slip inside the marina has a dedicated ultrasound-based sensor for boat detection.



Figure 3.7: Commercial low-power wireless sensors for boat monitoring and boat presence detection: Falco Boat (left) and Falco Presence (right).

to evaluate the Blip algorithm.

The Falco Presence device is a low-power wireless sensor that is capable of detecting, in real-time, whether a slip is occupied. We install one of these device at each slip inside the marina (Fig. 3.8). Falco Presence device is equipped with a 2.4 GHz System on Chip (SoC), PCB antenna and an ultrasound sensor, powered with a 3.6 V battery. The sensor outputs a 42 kHz ultrasonic signal for measuring the distance to an obstacle, in this case a boat. In the current version, Falco Presence is configured to trigger its ultrasound sensor every 5 min. Once the ultrasound distance measurement is performed, the device sends the raw data to the gateway without further processing. The data is then sent to the MQTT server, and processed by a boat presence detection algorithm. The output of this algorithm is displayed on a real-time map of the entire marina, accessible through the Falco application.

Falco Boat is a device that monitors a boat within the marina. Similar to Falco Presence, this device communicates wirelessly with other sensors inside the IoT network and sends the data to the cloud. Falco Boat is able to detect events such as fire, intrusion, tilt and shock. It also periodically measures the temperature and humidity and sends the



Figure 3.8: Presence sensor for boat detection inside a smart marina.

data to the gateway. This device is powered with 3 V (2x standard AA batteries) and is easily mounted inside the boat’s cabin. It also operates at 2.4 GHz band, forming a mesh network with other Falco devices. We use its MAC address as a unique identifier of the boat, in which we install the device. Additionally, the IoT infrastructure inside the marina generates events when the Falco Boat joins or disconnects from the network. We use this information to determine whether the boat enters/leaves the marina network.

As we previously mentioned, the communication protocol standard used in Falco IoT networks is similar to 6TiSCH. One of the most significant features of this standard is the addition of time-slotted channel hopping (TSCH) [117]. TSCH allows devices to coordinate their transmissions in a way that avoids collisions and improves reliability. The sensor are time-synchronized, which reduces the amount of time sensors spend listening for the incoming transmissions. This of course leads to significant reduction of their power consumption. Most of the time sensors are in sleep mode, waking up for a couple of milliseconds to send or receive a packet. Thanks to the efficient design of Falco Presence sensors and its firmware, it can achieve over 3 years of autonomy, powered with a 2.4 Ah capacity battery.

All nodes in an IEEE802.15.4e TSCH network maintain synchronization to one another. Time is cut into timeslots, each typically 10 ms long. Even in the absence of data, a TSCH mote sends an “empty packet” to its neighbor, typically every 30 s. It sends that packet at a very specific time inside a timeslot, called `TsTxOffset`. The receiving mote timestamps when it receives the start of that packet; it can be different from `TsTxOffset` because the two neighbor motes might have drifted in time. The receiving mote indicates that offset in a field inside the acknowledgement frame; the transmitting mote uses that information to re-align (“resynchronize”) the edge of the timeslot to that of the receiver. The crystal oscillators used by motes to keep track of time drift at a rate of 10–30 ppm (“parts per million”). Using different drift compensation techniques, even by re-synchronizing only every 30 s, commercial TSCH implementation exhibit a maximum de-synchronization of 15 μ s across the entire network [117]. We use this strong networking synchronization in WELOC.

3.2.3 Mobile Robots

We implement RRDV state machine (Chapter 7) on nRF52840-DK boards. We use one nRF52840-DK connected to a computer as a gateway; the others are installed inside the robots. The nRF52840 SoC has a 64 MHz ARM Cortex-M4 processor and supports different 2.4 GHz radio standards, such as BLE and IEEE 802.15.4. In this implementation, we use the BLE LR physical layer at 125 kbps, but implement our own protocol stack, which we detail in Chapter 7. The nRF52840 is equipped with PPI that allows precise synchronization between peripherals, for example timers, radio, General Purpose Input/Output (GPIO), etc. This feature is crucial to our implementation of RRDV as it allows precise timing and eliminates the need for CPU activity to carry on tasks for synchronization. In our case, we chain all events that are shown in Fig. 7.3 using PPI in order to achieve tight time-synchronization of the system. This is essential for good performance: as we are measuring distance using the ultrasound signals, we



Figure 3.9: The HC-SR04 is ubiquitous in robotic platforms to measure distance to obstacles. It is very easy to find and very cheap. RRDV re-uses it to detect encounters between robots. Note that the CWL-1601 is an equivalent sensor, operating at 3.3 V.

need synchronization accuracy below $100 \mu\text{s}$ to have cm-level distance accuracy. In order to verify the synchronization error, we trigger a pin on each robot and observe them using an oscilloscope. We collect 1000 samples; the mean absolute synchronization error is 0.05 ns with a Root Mean Square Error (RMSE) of 109 ns. This indicates that our implementation, and the hardware support of the nRF52840, offer a level of synchronization which is perfectly compatible with our application.

In RRDV, we use a well-known, low-cost, ubiquitous HC-SR04 sensor. As shown in Fig. 3.9, the HC-SR04 has two logical pins. The Trig pin is an input pin to the HC-SR04; the nRF52840-DK sends a $10 \mu\text{s}$ pulse to start the ultrasound transmission. The Echo pin is the output pin of the HC-SR04; the sensor encodes the measured distance in the pulse width of the echo pin. According to the sensor’s datasheet, $58 \mu\text{s}$ pulse width corresponds to 1 cm distance. We measure the sensor’s field of view by having two HC-SR04 face one-another. We move one along a 1 m cone from the other, until they stop receiving each other’s ultra-sonic pulse. This happens at a relative angle of 20° , indicating their field of view is a cone of aperture 40° .

To test our approach for robot encounter detection we use five off-the-shelf Exost HyperDrift Radio Controlled (RC) cars. The cars communicate with their remote controllers using a proprietary 2.4 GHz protocol allowing up to 10 cars to be driven at the same time. Even though the RC cars and the RRDV devices both communicate on the same frequency band, we have not noted any interference between them. As shown in Fig. 3.10, we install an nRF52840-DK connected to a HC-SR04 inside each car’s chassis. In this experiment, RRDV is completely independent from the RC car.

We place five cars in a $7 \times 4.2 \text{ m}^2$ area, each remote controlled by five volunteers. A computer is on the side, running the software, and having the nRF52840-DK and HC-SR04 in each car take ultrasonic distance measurements as the cars are driven around in random patterns. During the experiment, we place a GoPro HERO Black 10, 5 m above the area and record a video at 4K 30 fps. The entire experiment takes 12.5 min. Fig. 3.11 presents a live screen capture of the experiment.

We place large ArUco markers [118] on top of each car, so we can determine the position and orientation in each frame of the video using Computer Vision (CV). We

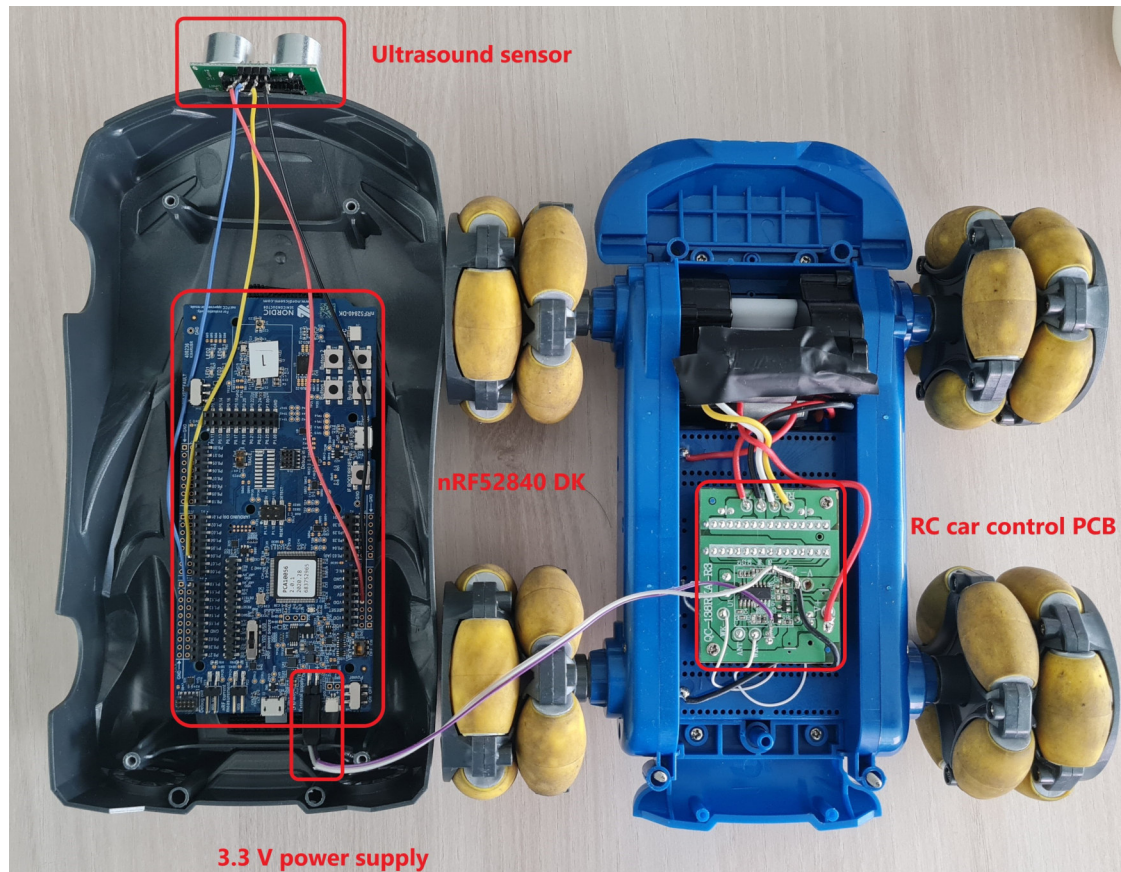


Figure 3.10: A Radio Controlled car (Exost HyperDrift) equipped with an nRF52840-DK and a HC-SR04. We used five of these to evaluate the performance of RRDV.

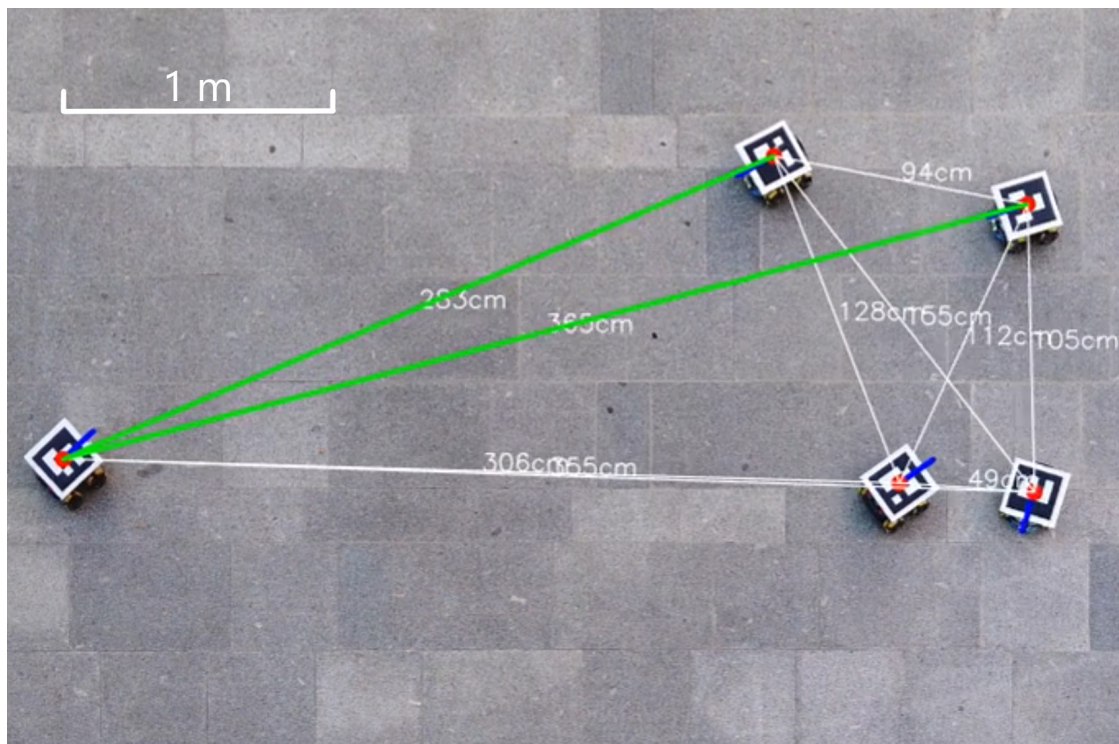


Figure 3.11: In our experimental evaluation, five robots drive around randomly. RRDV detects when two robots are facing one another. We call this an “encounter”; it is depicted as a green line.

choose ArUco markers because they are easy to visually track, are well supported by the OpenCV [119] computer vision library, and provide both position and orientation data. To determine in the video when two cars are facing one another, we “draw” 40° cones in front of each ArUco marker, representing the field of view of the HC-SR04. If two cars are contained in each other’s cone at the same time, with no obstacle in-between, we consider that as an encounter, which we use as ground truth. In case a car is involved in two or more encounters, we consider only the one with the shortest distance as valid. We place visible markers in corner of the area to correct the camera perspective with a homography transformation in the CV software. We have the computer display a large timer on its screen, and make sure the camera records that, so we can efficiently synchronize the video to the RRDV data.

3.3 Summary

In conclusion, we believe that our decision to perform real-world experiments and use real-world datasets is motivated by the need for a reliable and accurate localization system. Our analysis of the problem highlighted the limitations of simulations and the importance of testing in a real-world environment. We use the existing IoT network in the marina to develop a solution that is cost-effective and reliable, and our use of real-world datasets validated the accuracy and reliability of our boat identification algorithm. Furthermore, we use the hands-on approach to design a system that is able to detect encounters between robots in a swarm, which is a promising direction for future research. The methodology we presented in this chapter outlines the steps we took and tools we used to develop and evaluate our solutions, and we believe that it can be used as a framework for future research in this area.

Chapter 4

Performance of BLE AoA Estimation and UWB Ranging

Parts of this chapter were published as part of the following article: *Constrained Localization: a Survey*. [Trifun Savić](#), Xavier Vilajosana, Thomas Watteyne. **IEEE Access**, volume 10 (2022): 49297-49321.

Key Takeaways: This chapter presents a series of hands-on experiments that we perform with the popular RF-based technologies, used in RTLS systems today. We conduct experiments with commercial products based on Bluetooth AoA and UWB TWR. More specifically, we use Texas Instruments and Nordic Semiconductor commercial AoA evaluation kits, and Decawave UWB evaluation boards. We perform experiments with the provided equipment as-is, experiencing first-hand the various constraints these technologies have. Obtained results allow us to develop an intuition for the accuracy in angle and ranging estimations of the mentioned commercial products.

4.1 Introduction

This chapter presents a series of hands-on evaluations of RF-based commercial products used for RTLS. Because we want to dive deeper into RF-based technologies and experience first-hand their performance, we conduct experiments with some of the popular Angle of Arrival and Time of Flight solutions on the market today. As we already discussed in Chapter 2 these technologies show promising results and are the starting point of our research. Experiments show the performance of these technologies, when using off the shelf products, without any additional filtering algorithms.

We want to understand if we can use similar techniques in the use cases presented in Section 1.6. We do not perform an in-depth comparison of the commercial RTLS

products. The goal of these experiments is to build up an intuition regarding the performance of these popular technologies. We obtain results with hardware, firmware and software provided by manufacturers as is, without additional work done to improve their performance.

Contributions of this chapter are twofold.

- We perform hands-on experiments of commercial Bluetooth AoA- and UWB-based technologies for RTLS. These experiments show first-hand the capabilities of these technologies as provided by the manufacturer, without additional filtering schemes employed from our side.
- We discuss the performance of the tested solutions and highlight their constraints. We argue that there is no perfect technology for RTLS and that we have to employ additional filtering algorithms and/or combine different technologies.

This chapter is organized as follows. Sections 4.2 and 4.3 show the AoA estimation error from Texas Instruments and Nordic Semiconductor, respectively. Section 4.4 presents the accuracy of the Decawave UWB ranging. Section 4.5 concludes this chapter.

4.2 Texas Instruments Angle of Arrival

We verify AoA estimation using the Texas Instruments evaluation kit in a realistic scenario. The testing site is a two-bedroom apartment, with the antenna array positioned in the living room, allowing AoA estimation of the mobile device at 2 m distance (LoS) and 4 m distance (NLoS) from the antenna array center (Fig. 3.4). In order to provide a realistic scenario, we perform the experiment in the presence of Wi-Fi and multiple wireless devices such as smartphones and laptops. The testing site is such that the antenna is placed on the tripod, the mobile device in “front” of it, as shown in Fig. 4.1. At 2 m distance, we perform AoA estimation with a step of 10° . At 4 m distance, we measure the angle for a smaller number of measurement points, due to the size of the apartment. The position of the antenna array is 2.1 m above the apartment floor, with the mobile device located on the floor. We obtain the ground truth of the angle by attaching one end of a fishing wire to the center of the reference circle below the antenna array, and the other end of the wire to the mobile device. The reference circle contains the angles with 10° steps, for measuring the ground truth. Distance is measured from the center of the reference circle to the antenna of the mobile device.

We perform AoA estimation using antenna array 1 on the BOOSTXL-AOA kit which covers angles from -45° to 135° (Fig. 3.1). The antenna array has three dipole antennas positioned linearly. This allows only for the azimuth angle estimation. As mentioned before, default software for AoA estimation gives raw angle measurements; we obtain the azimuth angle at each measurement point by logging and averaging the results in a 30 s time window.

At 2 m distance from the antenna array with LoS (Fig. 4.2) the raw AoA estimations shows big oscillations of the absolute error in the azimuth angle estimation, especially



Figure 4.1: BOOSTXL-AOA angle of arrival estimation test setup.

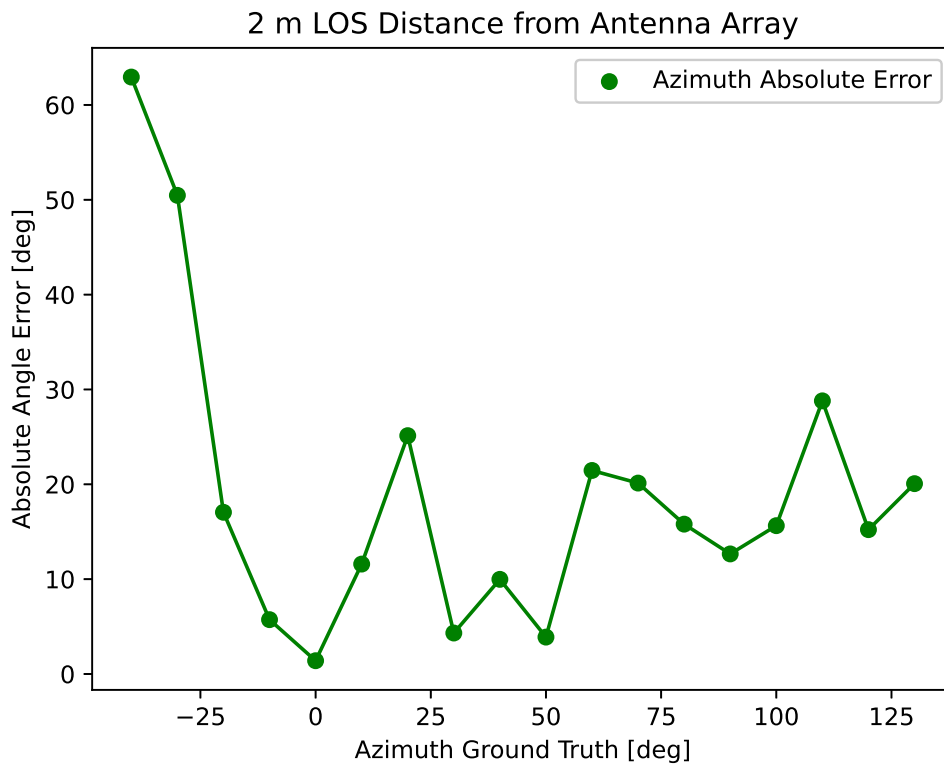


Figure 4.2: Absolute AoA estimation error with mobile device located at 2 m distance from the antenna array in LoS using BOOSTXL-AOA.

when the mobile device is located at the angles closer to -45° and 135° . These oscillations in the AoA estimation result in an RMSE of 24.4° .

Fig. 4.3 shows the absolute azimuth error of raw AoA estimations in NLoS scenario at 4 m distance. The NLoS experiment gives better result compared to the 2 m distance because we had to do AoA estimation at a smaller number of measurement points. Therefore we couldn't estimate the angles on the far left and far right part of the antenna array which cause the larger errors. The RMSE in this case is 16.81° .

This experiment shows how AoA estimation is very sensitive and can give huge errors in indoor environments, especially in the presence of other wireless devices and multi-path reflections. These results clearly indicate that raw AoA measurements can only give us a general idea of the direction of the signal. A possible way of improving the results could be to employ some filtering algorithm, such as an EKF. Also, the results show that the measurements are severely corrupted, almost random, when the mobile device is almost parallel to the Antenna array 1 on both sides (less than -20° , more than 110°). This is due to the linear position of the antennas in the antenna array. In LoS conditions, we take more measurement points near parallel to the antenna array compared to the

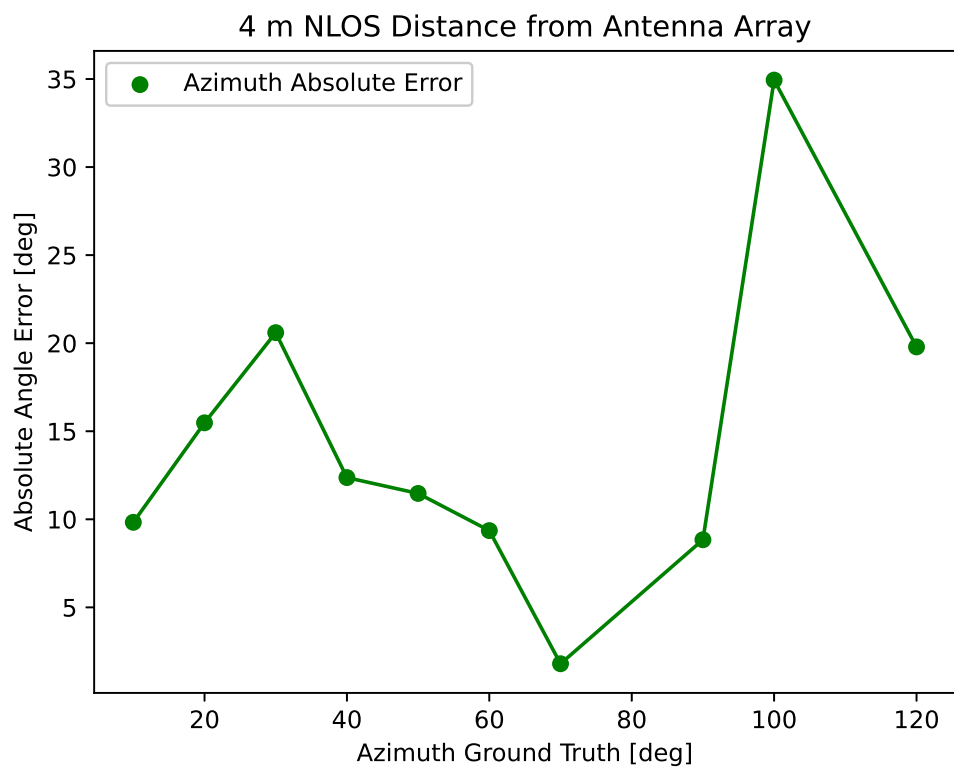


Figure 4.3: Absolute AoA estimation error with mobile device located at 4 m distance from the antenna array in NLoS using BOOSTXL-AOA.



Figure 4.4: Nordic Semiconductor angle of arrival estimation test setup.

NLoS, which causes a larger RMSE. When we calculate the RMSE in the LoS at the same measurement points as in the NLoS experiment, we get the expected result of better performance in LoS condition. The experiment in the Section 4.3 shows that we can avoid the issue of large errors near parallel to the linear antenna array by using the antenna array with the multiple antennas positioned in a plane.

4.3 Nordic Semiconductor Angle of Arrival

We perform AoA estimation with Nordic AoA evaluation kit in the same realistic indoor scenario and configuration as in Section 4.2. The testing site allows AoA estimation at 2 m LoS and 4 m NLoS distance, as shown in Fig. 3.4. We position the antenna array 2.1 m above the floor in the living room of the two-bedroom apartment (Fig. 4.4). The mobile device is located on the floor attached with the fishing wire to the center of the reference circle that contains the ground truth angles. Similar to the experiment with Texas Instruments' direction finding kit, we do the AoA estimations in the presence of WiFi and other wireless devices.

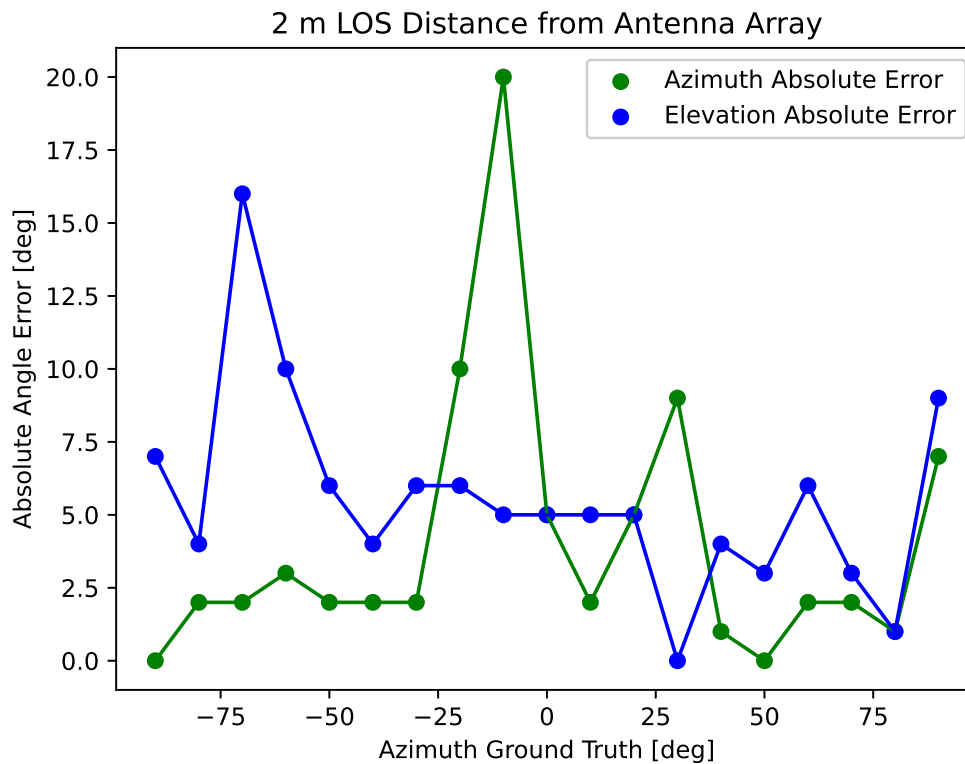


Figure 4.5: AoA estimation absolute azimuth and elevation error at 2 m distance between the mobile device and antenna array in LoS, using Nordic Semiconductor kit.

The antenna array with 12 antennas in a plane configuration can estimate azimuth angle in a 0° to 360° range and elevation range is from 0° to 90° . However, in this experiment, we are doing the estimation with azimuth ground truth from -90° to 90° . Elevation angle ground truth remains constant if the distance between mobile device and antenna array doesn't change. We obtain the azimuth and elevation angle at each measurement point by taking the filtered result of the angle estimation.

Fig. 4.5 shows the absolute error of azimuth and elevation angles at 2 m LoS distance between the mobile device and the antenna array. In this test, most of the AoA estimations of azimuth and elevation are below 10° absolute error with small number of outliers. The RMSE of azimuth and elevation is 6.17° and 6.48° , respectively.

In the case of AoA estimation at 4 m NLoS, the angle estimation results are inferior. Equivalent to the experiment in Section 4.2, we couldn't estimate AoA at every test point due to the size of the apartment. We show the absolute azimuth and elevation error for 4 m NLoS distance in Fig. 4.6

In this experiment, we can clearly see the benefits of using filtering algorithms in AoA estimation. A filtering algorithm removes outliers and improves the overall accuracy of

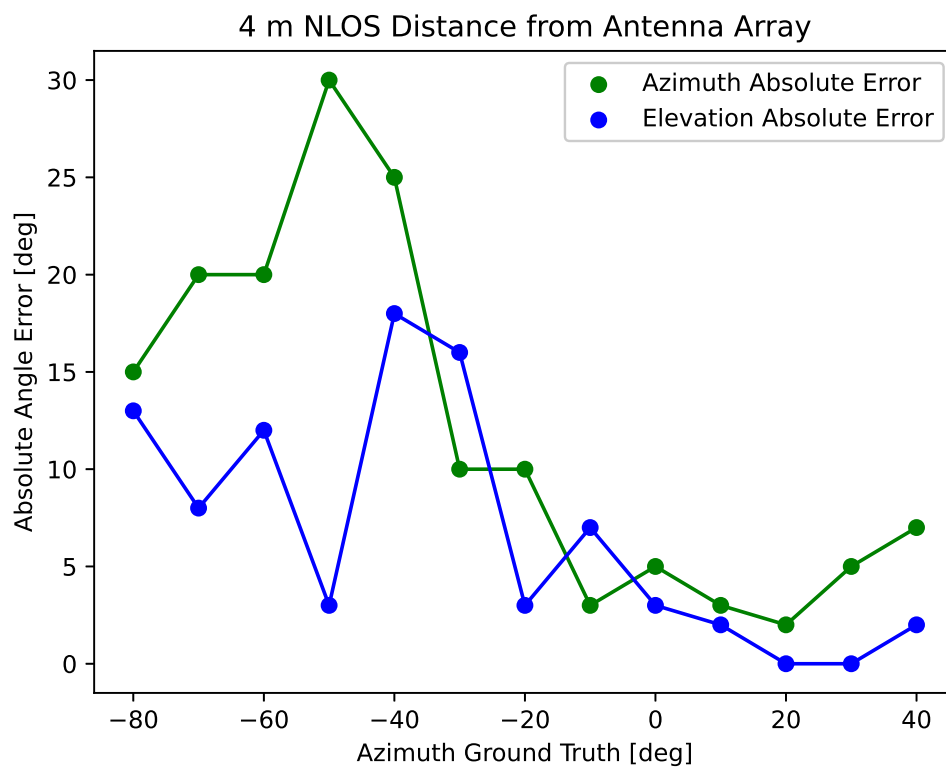


Figure 4.6: AoA estimation absolute azimuth and elevation error at 4 m distance between the mobile device and antenna array in NLOS, using Nordic Semiconductor kit.

the estimation. As we can see from the results, the error is significantly lower when comparing filtered AoA to raw AoA measurement obtained in the experiment with Texas Instruments evaluation kit in Section 4.2. Also, results show that having the antenna array with 12 antennas positioned in a plane configuration resolves the issue of outliers when the mobile device is placed near-parallel to antenna array as it can estimate angles in the 0° to 360° range. The downside is the complexity of the antenna array and its bigger dimensions. Finally, as in Section 4.2 for the NLoS scenario, the AoA estimation degrades because of strong multi-path reflections.

4.4 Decawave Ultra-Wideband

In order to evaluate the ranging accuracy of mentioned Decawave UWB module, we perform the outdoor ranging test in the Bois de Vincennes, a forested park in Paris. For this test, we use two Decawave DWM1001-DEV development boards which run Single Sided Two Way Ranging firmware provided by Decawave. Two devices exchange messages in LoS conditions. One device is the anchor with fixed position which sends the ranging message to the mobile device and waits for the response. After the anchor receives the response back from the mobile device, it calculates the distance using the time recorded for the round trip of the radio signal. We take the ranging measurements at multiple points with the anchor fixed on a tripod and the mobile device moving away, as shown in Fig. 3.5. 100 ranging measurements are taken at each measurement point, taking 100 ms for each one ranging. We use a laser distance meter to obtain the ground truth for distances smaller than 10 m between the anchor and the mobile device. For greater distances we use distance measuring tape.

Fig. 4.7 shows ranging measurements from 2 m to 40 m between two devices. Results show the distance measurement error below 1 m in most cases, with some outliers being above 1 m. The range estimation in this experiment gives positive error only. This is due to the hard coded value of Tx to Rx antenna delays. In the case of the Decawave TWR firmware these values are set to give a positive range estimate error.

We find that for reliable distance estimation using the Decawave DWM1001 module the maximum range between devices in the open field is 40 m. Farther than 40 m, we did not register packet receptions, which implies that the TWR ranging cannot be performed. In order to achieve sub 0.5 m ranging accuracy we need to develop antenna delay calibration procedure for Decawave UWB modules. Antenna delay calibration is also recommended by Decawave for applications that require sub 30 cm ranging accuracy [120]. Thus, ToF estimation will include the time needed for a signal to leave from the transceiver IC to the module's antenna and vice versa.

4.5 Conclusion

By presenting a hands-on evaluation of commercial products for RTLS, we give an insight into basic capabilities of Bluetooth AoA estimation and UWB ranging. The goal of these experiments is not to serve as an exhaustive comparison between different commercial

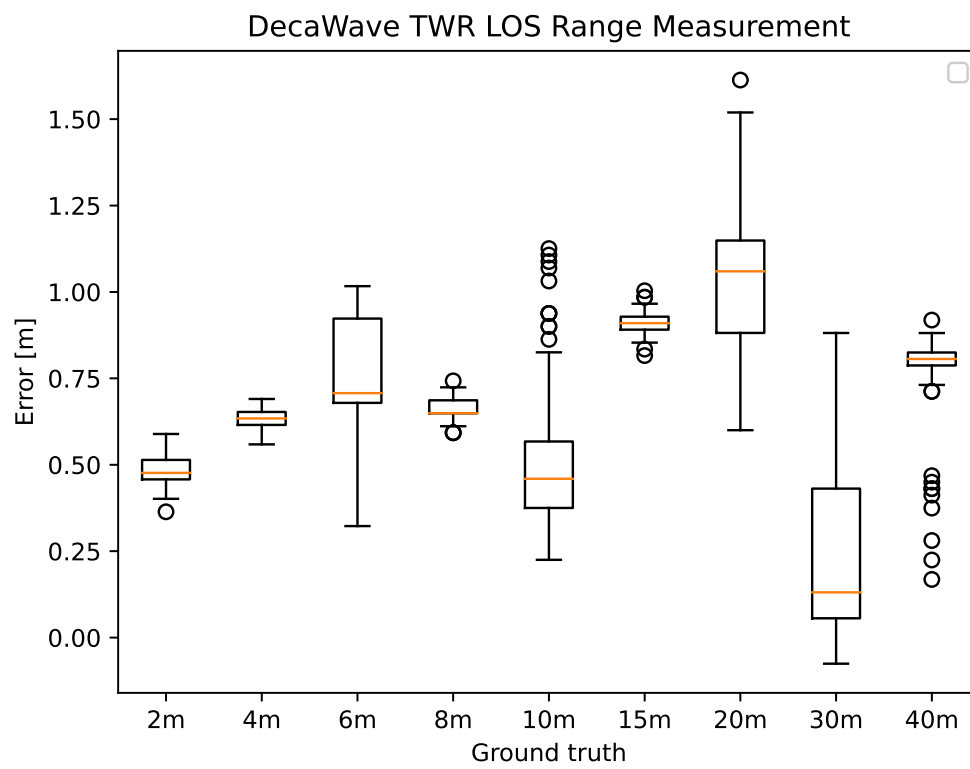


Figure 4.7: Box plot of TWR LoS distance measurement error between the two DWM1001-DEV.

solutions. Rather, we want to foster an intuition about the performance of ToF and AoA techniques, as a necessary step before selecting specific technology for RTLS. Commercial products used for these tests allowed us to quickly examine their constraints and develop our expectations.

We evaluate AoA using Texas Instruments and Nordic Semiconductor evaluation kits. From the two hands-on experiments with AoA estimation we can draw several conclusions. Results confirm that we need LoS for better AoA estimation in an indoor environment. Strong multi-path reflections and the presence of other wireless devices severely degrade the quality of the measurements. Raw AoA measurements are noisy and we need to employ some filtering algorithm in order to improve results. However, complex algorithms need higher computational power and affect energy efficiency, which is especially challenging with recourse constrained devices. Finally, there are different antenna array form factors. The number of antennas and their placement in the array has an important role on the measurements especially if we want to cover more area. This of course means more complex antenna array and bigger dimensions.

Hands-on evaluation of the UWB TWR technique using popular Decawave evaluation boards shows the range limits in outdoor LoS scenario. We measure a maximum distance of 40 m between two devices with stable communication allowing ranging between them. The ranging error gives us a sense of the accuracy using off the shelf devices and default firmware. If an application requires a sub-decimeter precision, a calibration procedure needs to be developed to include antenna delays in ToF measurements.

We need to highlight that we perform AoA and ToF experiments with only one anchor and a single mobile device. A realistic deployment would have many anchors in order to cover more area and lower the positioning error, and a carefully designed triangulation or trilateration algorithm in order to estimate the location of the mobile device. Researchers have to carefully examine application requirements in order to choose the baseline technology for RTLS. These requirements dictate the necessary accuracy, update rate, battery life and cost of the system. There is no perfect technology for localization. Therefore, we underline that the most important aspect when designing RTLS is the implementation of the best suited algorithms and possible combination of different technologies, all depending on the use case of localization.

Chapter 5

WELOC: Localizing Equipment in Marinas using Ultrasound

Parts of this chapter were published as part of the following article: *WELOC: Localization Equipment in Marinas using Ultrasound*.

Trifun Savić, Keoma Brun-Laguna, Thomas Watteyne. **Special session on Navigating the Opportunities and Challenges in Maritime IoT, IEEE World Forum on Internet of Things (WF-IoT)**, Aveiro, Portugal, 12–27 October 2023, *accepted*.

Key Takeaways: This chapter proposes WELOC, an ultrasound-based localization system for localizing objects in a marina environment. WELOC uses the already installed infrastructure of commercial IoT devices, fixed at each slip on the pontoons, used for boat presence monitoring. These devices are equipped with an ultrasound sensor, have known GPS positions and form a wireless, time-synchronized ($<15 \mu\text{s}$ synchronization error), mesh network around the gateway. Without impacting the main function of the smart parking system for boats, we propose a scheme to schedule when each ultrasound sensor is triggered. We design a mobile device, from an off-the-shelf ultrasound sensor, compatible with those already present in marinas. We synchronize the device with each ultrasound trigger in the marina, and collect the timestamped distance measurements. The location of the mobile device is then computed using trilateration. We test the ranging accuracy of the mobile device in the lab, where we achieve a 3.5 cm mean absolute error, with a maximum range of 10 m. We perform field testing for the ultrasound signal detection inside the marina, which is equipped with 471 presence sensors, one at each of its slips. We show that our mobile device successfully detects the ultrasound signal on the pontoons.

5.1 Introduction

As mentioned in Section 1.6.1, one of the specific use cases we focus on is the localization of boats and equipment in a smart marina environment [121]. Marinas are looking for localization system for knowing the location of: boats (to know if they are in the right place and to warn marina operators in case of an unexpected movement which could indicate theft), equipment (to know the location of an important asset or tool in order to improve efficiency) and workers (to ensure that they are safe and working on the right tasks). Additionally, by having real-time information about the location of boats and other watercrafts, marina operators can optimize the use of the pontoons. It can also help boaters navigate the marina and find their desired destination more easily.

In this chapter we propose WELOC, a localization system implemented on top of the commercial “Smart Parking for Boats” IoT solution deployed in the marina. By utilizing an already existing infrastructure of ultrasound-based sensors for boat detection, we propose a scheduling scheme for activating these fixed sensors. Without altering their main function for boat detection, we are able to re-use the ultrasound signal for distance calculation between the fixed sensors and a mobile device. We propose the use of an off-the-shelf ultrasound sensor for the mobile device, capable of detecting 42 kHz ultrasound signal present in the marina. We synchronize the mobile device with the presence sensors over radio, timestamp the measured distances and send it over the network to the cloud. We can then estimate the position of the mobile device through trilateration. In order to test our approach, we perform ranging experiments in the laboratory. We show the absolute distance error of 3.5 cm between the anchor and the mobile device, with the maximum range of 10 m between devices. We perform field testing in Sète marina in the South of France. Tests show that we are able to detect ultrasound signal on pontoons using the proposed mobile device. WELOC is designed as a software/firmware update to an existing IoT solution deployed in the marina. Thus, we avoid the deployment of the new infrastructure of anchor devices to enable the localization. Of course, WELOC can be used as-is in other parking deployments, indoor and outdoor.

This chapter is organized as follows. Section 6.2 defines the problem statement and presents the contributions of the chapter. Section 5.3 presents the Sète marina requirements for a localization system. Section 5.4 presents WELOC. We discuss the system architecture, mobile device design and show the ultrasound detection experiment in the marina. Finally, Section 5.5 concludes this chapter.

5.2 Problem Statement and Contributions

The intuitive approach, when designing a localization system for marinas, would be to use the Global Positioning System (GPS). GPS receivers are ubiquitous and we all have them in our cell phones, cars and boats, and it works well outdoors. However, we want to have sub 1 m localization accuracy with years of battery life for our marina use case. A standard GPS receiver cannot provide sub 1 m accuracy and is very power hungry [1].

Another approach could be to use the Received Signal Strength (RSS) measurement to calculate the distance between the two radio devices. When a device receives a radio packet from the transmitter it can obtain the RSS indicator, as most radio chips on the market provide this information “free of charge”. We could then use signal propagation model to estimate the distance between the two devices [14]. By estimating the distance to three or more transmitters we can trilaterate the position of the receiver, if the transmitters’ positions are known. Due to the the nature of the radio signals, multi-path and fading effects can seriously affect the distance estimations. For example, localization systems based on long-range radio technologies offer an accuracy of 100 m - 1 km [78]. A different approach can be the use of localization solutions that have been proposed for the indoor use, but could be considered for the marina use case. They combine fixed devices, pre-deployed at known positions (the “anchors”) through which tags (the “mobile devices”) move. The mobile devices are located by making measurements relative to the anchors: either distance measurements (this is the case of Ultra Wide Band – UWB [44], [82]), or angle measurements (this is the case of the Angle of Arrival – AoA – standardized by Bluetooth in 2019 [50]). Several comparative studies highlight the trade-off between the localization accuracy obtained, and the density of the anchors [122], [123]. However, the main problem of these solutions is that they require the deployment of dedicated anchors (which form an infrastructure), and the power supply of these anchors, which remain active all the time and thus consume too much to be powered by batteries.

We focus on a specific use case of marinas equipped with Falco IoT solutions. Falco is a company that develops and commercializes IoT networks and services for marinas [68]. One of the solutions Falco creates is a service that detects when a slip inside the marina is occupied by a boat. We install Falco Presence sensors at each slip to monitor the presence of a boat, using an ultrasound sensor for distance measurement. These battery-powered devices communicate over radio and form a wireless, time-synchronized, mesh network around the central gateway. The distance measurements from all sensors inside the marina are sent to the cloud, where the presence detection algorithm outputs a real-time occupancy of slips on a map. The intuition here is that we already have all the components inside the existing IoT network to enable localization. We have fixed devices with known GPS positions (Falco Presence), all devices are equipped with ultrasound sensors (possibility of distance calculation using Time of Flight – ToF) and Falco IoT network is time-synchronized (allowing precise scheduling of the ultrasound measurements). Therefore, if we add a tracking device inside the marina, which is synchronized with the network and capable of receiving ultrasound signal from the fixed sensors, we can estimate its position relative to them, using trilateration.

Contributions of this chapter are threefold.

- We propose WELOC, an ultrasound-based localization system for locating objects in a smart marina environment. This system is implemented in firmware/software and uses the existing IoT, fixed, battery powered, infrastructure already present in the marina.
- We design a mobile device, capable of receiving/transmitting ultrasound and radio

signals, compatible with those inside the IoT network. We use an off-the-shelf ultrasound sensor, synchronize it over the radio, and transfer the measured values to the cloud for trilateration.

- We evaluate the mobile device in the lab and inside the marina. We show the 3.5 cm mean absolute ranging error in the lab environment and 10 m range, assuming perfect synchronization. Field testing in real-life marina presented in Section 3.2.2 shows that we are able to detect ultrasound signal from the presence sensors, with the mobile device located on the pontoons inside the marina.

5.3 Sète Marina Requirements

Different applications place different requirements on the localization system; it is important to find the best trade-off between localization technique and technology used [124]. The marina use case described in Section 1.6.1 sets the quantified requirements on accuracy, power consumption, location update rate and absence of infrastructure. The main objective is to address the need to deploy anchors in a localization system and the need to power these anchors. Specifically, we are setting the following requirements to our localization system:

1. we need the localization error to be less than 1 m;
2. we need the location update at least every 5 minutes;
3. we need to stay both low-power and wireless, and not use Wi-Fi and Ethernet networks that might be present in some marinas;
4. we need all deployed infrastructure to be battery-powered, and to run for at least 3 years.

5.4 WELOC

The commercial Falco solution for monitoring the slip occupancy in a marina contains all the necessary building blocks for a localization system. First, the presence devices installed under the pontoons have a known GPS position and can serve as anchors relative to which we estimate the position of a mobile device. Second, these devices are equipped with a ultrasound sensor, which is a well known technology for sound-based localization systems. Third, Falco network is time-synchronized, which allows the precise time scheduling of the ultrasound sensors. Therefore, the core intuition behind WELOC is to upgrade the Smart Parking solution from Falco and enable localization.

WELOC uses the available infrastructure of presence sensors in the marina as fixed anchors. Since all presence sensors have a known GPS location, knowing a distance between the mobile device and at least three fixed anchors allows to estimate the position of the mobile device. We can perform the trilateration to determine the location of the mobile device. In Fig. 5.1 we show the block diagram of the system. WELOC consists

of the following: presence sensors (fixed anchors), mobile device (device to be tracked) and a gateway.

The proposed system does not alter the main purpose of the Falco Presence devices, explained in Section 3.2.2. We trigger the ultrasound measurement of each device with an offset that depends on its unique identifier. Fig. 5.2 shows the proposed schedule. We want to synchronize the mobile device with each Falco Presence in the marina. In WELOC, the ultrasound triggering functions in a Time Division Multiple Access (TDMA) fashion, where one time slot for ultrasound measurement is 30.2 ms. We take 20 μs for the ultrasound pulse trigger (writing a HIGH voltage level to the sensor's trigger pin) and 30 ms for listening for the echo (measuring the ultrasound ToF i.e. distance between the mobile device and a single Falco Presence). We chose the 30.2 ms time window due to the limitations of the ultrasound receiver on the mobile device, which the range limit of 10 m. In one ultrasound ranging cycle, each Falco Presence device in the marina triggers its ultrasound sensor only once. The device measures the distance to an object and performs the boat detection. In the same time, its reflected signal is also picked up by the mobile device. The mobile device triggers the ultrasound reception each time a Falco Presence device triggers an ultrasound measurement. This means that the mobile device triggers the ultrasound reception n times for n number of presence sensors in the marina, where duration of one ultrasound ranging cycle is $n * 30.2$ ms. In its current implementation of WELOC, the fastest update rate of localization in Sète marina is 15.1 seconds, which satisfies the application Requirement 2, set in Section 5.3.

When the mobile device records a distance measurement, it also timestamps it. This is done for each recorded measurement in one ultrasound ranging cycle. Let's assume that in one ranging cycle the mobile device records four distance readings. This corresponds to the four Falco Presence device in its vicinity, which have triggered the ultrasound for boat detection. Each distance measurement corresponds to the distance between a single Falco Presence device and the mobile device. These distances are transferred to the gateway after one ranging cycle, and forwarded to the cloud application. We compare the timestamped distance measurement with the ultrasound sensor trigger time to determine from which Falco Presence device the mobile device received the ultrasound signal. We then calculate the position of the mobile device relative to the Falco Presence devices using trilateration. WELOC does not rely on existing mains power infrastructure or Wi-Fi/Ethernet networks. The battery-powered Falco Presence devices, which are used as the anchors in WELOC, offer more than 3 years of battery autonomy. Therefore, WELOC satisfies the application Requirements 3 and 4, set in Section 5.3.

5.4.1 Mobile Device

The mobile device is equipped with a 2.4 GHz SoC and an ultrasound sensor. It is capable of time-synchronized communication with the existing wireless IoT devices inside the marina. In order to avoid additional costs for designing a custom ultrasound receiver for the mobile device, we use an off-the-shelf sensor. In our previous work, we show that it is possible to achieve cm-level ranging accuracy by synchronizing off-the-shelf ultrasound sensors, primarily designed for sensor to object distance measurement [125].

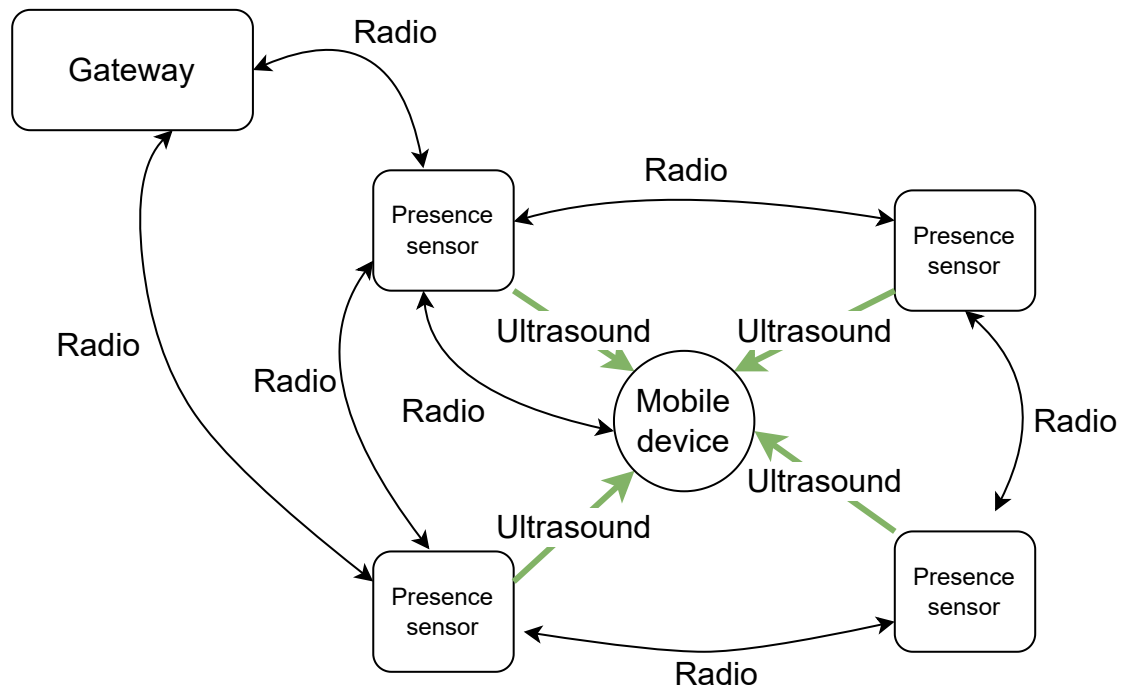


Figure 5.1: System block diagram showing the presence sensors and the mobile device, reporting boat detection and timestamped ultrasound ranging measurements to the gateway, respectively.

We identified the 42 kHz ultrasound sensor, MaxBotix - MB1603, operating at the same frequency as the ultrasound sensors on the Falco Presence. MB1603 has two transducers, one for transmitting and one for receiving the ultrasound signal. If we cover the transmit transducer on the mobile device with tape/foam the sensor cannot perform distance measurement. Its echo signal will never reach the receiver transducer. However, the functionality of the sensor for measuring the round-trip time is not disabled. If we synchronize the ultrasound transmission on the anchor device (Falco Presence) and on the mobile device (MB1603), we can measure the distance between the two sensors. In order to obtain the actual distance we multiply the output of the sensor by 2, since there is no round-trip time. The MB1603 is designed to measure distances up to 5 m, hence the mobile device maximum ranging of 10 m.

We test the ranging accuracy of the mobile device in the laboratory (Fig. 5.4). The mobile device's transmitter is covered with tape and has only the receiving transducer active. In this test, the anchor device is a single transducer MaxBotix - MB1010 sensor. It has the same transducer characteristics as the ultrasound sensors deployed in the marina. Both device trigger the ultrasound measurement by having the PIN 4 at high voltage level for more than 20 μ s. We want to test the accuracy of the ranging in ideal case, assuming perfect network synchronization. We connect both devices with a long cable in order to trigger them with a single switch. When active, the switch pulls the trigger pins on the anchor and the mobile device HIGH at the same time. Fig. 5.3 shows the

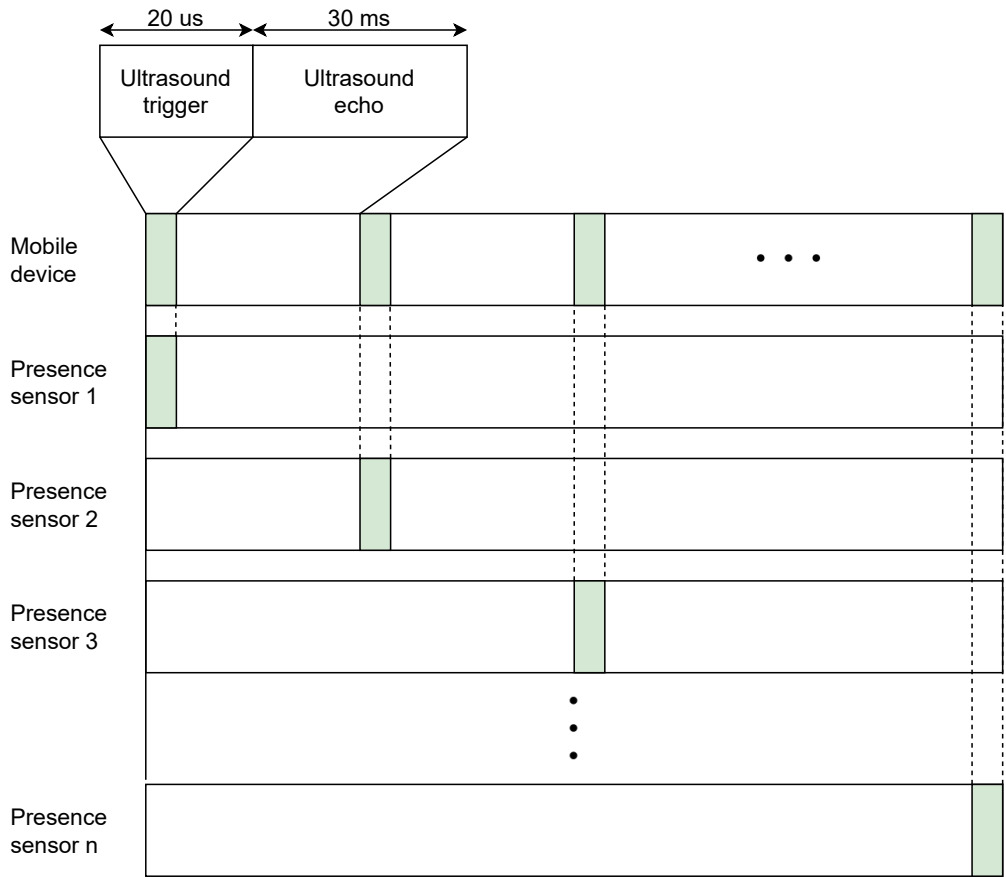


Figure 5.2: WELOC ultrasound trigger schedule.

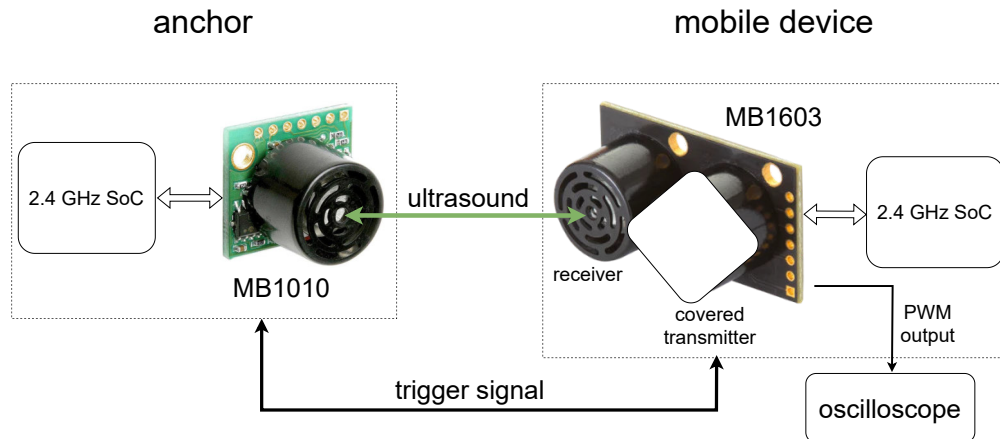


Figure 5.3: Block diagram diagram of the ultrasound ranging test in the lab. MB1010 (left) corresponds to the fixed presence sensor (anchor) inside the marina. MB1603 (right) corresponds to the ultrasound receiver on the mobile device. In this test, the two devices are connected with long cable and share the same trigger signal.

test configuration. In order to obtain the results, we use the oscilloscope to measure the PWM output on the mobile device. Here, $1 \mu\text{s}$ duration of the PWM signal corresponds to 1 mm distance to an object. We multiply the output by 2 to obtain the actual distance. For obtaining the ground truth we use laser distance meter.

Fig. 5.5 shows the absolute ranging error. We obtain the mean absolute distance error of 3.5 cm. As expected from the sound-based ranging systems, we achieve cm-level accuracy up to 10 m of distance between the anchor and the mobile device. In this experiment we have no synchronization error accounted, as we assume perfect synchronization and use a single switch to trigger both sensors. As explained in the Section 3.2.2, the deployed IoT network in the marina is time-synchronized, with synchronization error of $< 15 \mu\text{s}$. The sub $15 \mu\text{s}$ level synchronization corresponds to approximately 5 mm distance error for the sound-based distance measurements. As our localization accuracy requirements are sub 1 m error, the proposed architecture can be used to meet the application Requirement 1, set in Section 5.3.

5.4.2 Field Testing

In order to verify that the WELOC system can be implemented in the real-life marina use case, we perform the ultrasound detection with the mobile device in Sète marina, described in Section 3.2.2. Since the Falco Presence devices are installed on the pontoons, riveted below the floor level, detecting the ultrasound on the pontoons can be challenging. Therefore, we perform this test to verify that we are able to receive the ultrasound from the Falco Presence devices, while walking on the pontoons with the handheld mobile device. The purpose of this experiment is to check the feasibility of WELOC with a hands-on experiment. Therefore, we do not timestamp the distance measurements obtained by the mobile device, but rather check for the presence of the ultrasound on



Figure 5.4: Ultrasound ranging test setup located in the corridor of the research laboratory.

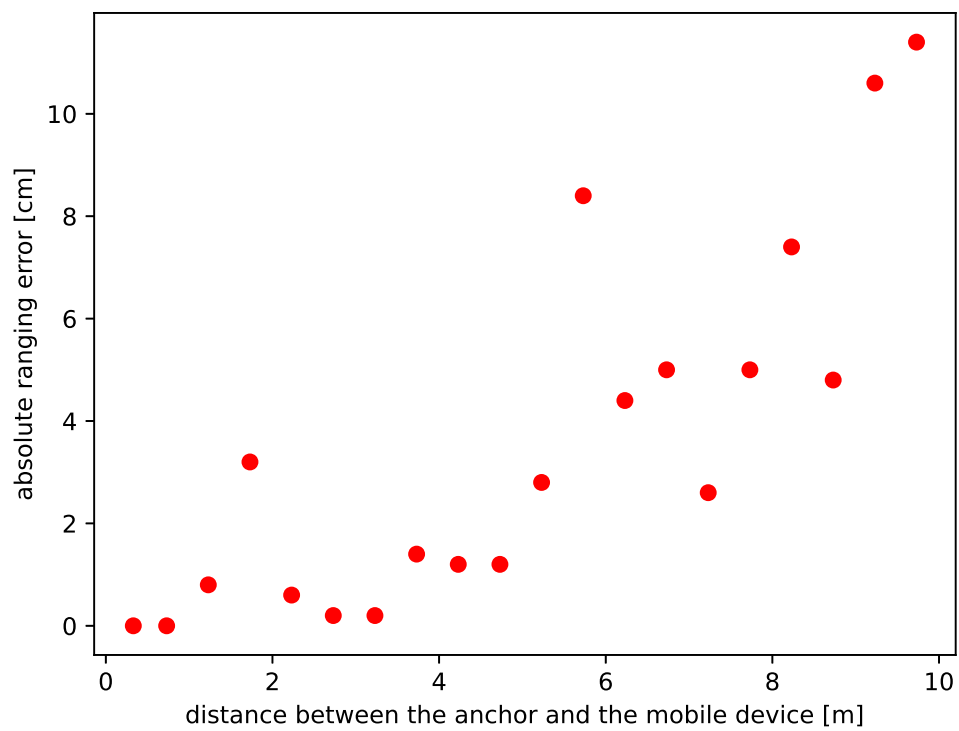


Figure 5.5: Absolute ranging error between anchor and mobile device. Measurements are collected from the PWM output pin of the mobile device, while the ground truth is obtained by a laser distance meter.



Figure 5.6: Experimental setup for ultrasound detection. We monitor the analog output pin of the mobile device to register an ultrasound signal reception.

the pontoons.

Fig. 5.6 shows the experimental setup for the ultrasound detection in the marina. We configure the Falco Presence devices to trigger the ultrasound ranging every 5 s. This allows us to perform ultrasound detection with faster rate, compared to the default Falco Presence operation (ranging every 5 min). We use the oscilloscope to capture the value of the analog output pin of the mobile device. When there is no signal detected we observe 3 V output. When an ultrasound signal is detected the analog signal drops below that value, which means that we captured an ultrasound signal coming from a Falco Presence. We perform the experiment at the pontoon E, inside the Sète marina.

We run the experiment with 28 Falco Presence devices reconfigured to trigger ultrasound every 5 s. We hold the mobile device in hand, 1.5 m above the pontoon. For each position of the mobile device we monitor the analog output pin. We point the mobile device to different directions, as shown in Fig. 5.7. We can see that, for each of the positions depicted, the mobile device can detect the ultrasound signal on the pontoon. This experiment shows that the implementation of WELOC is feasible in a real-life marina use case.

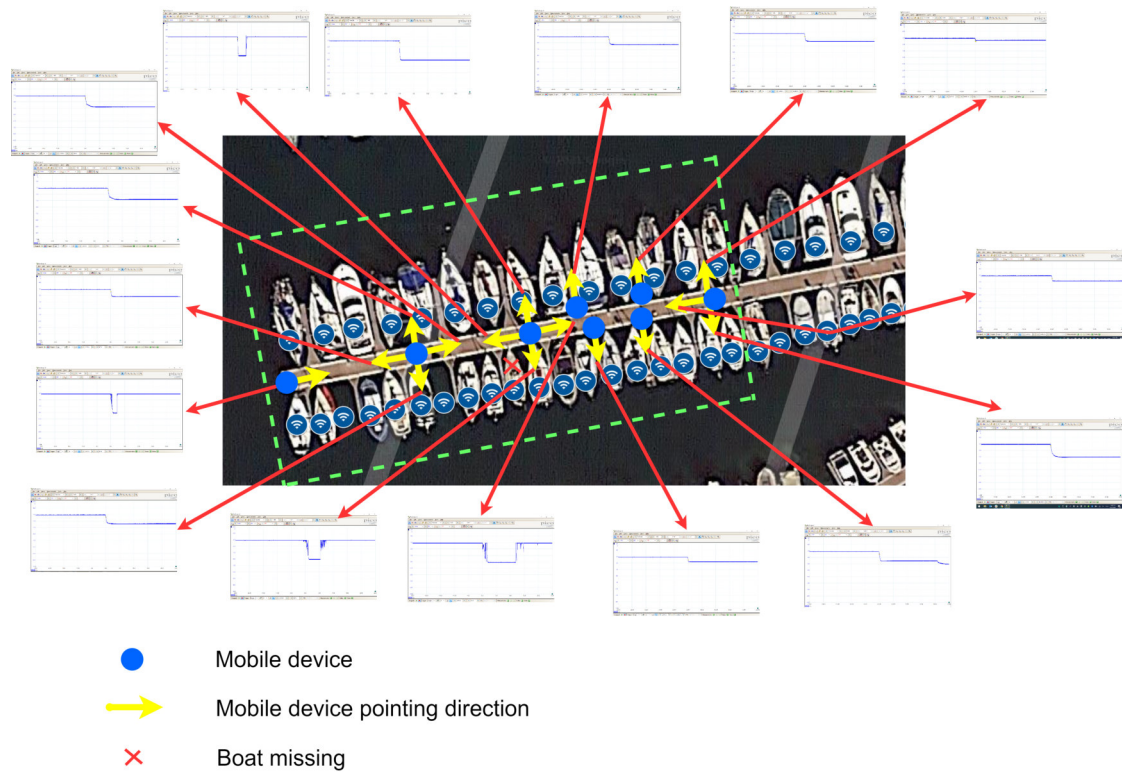


Figure 5.7: Diagram shows the ultrasound signal detection in the Sète marina in the South of France. We depict the positions and orientations of the mobile device on the pontoon during the experiment. The mobile device successfully detects the ultrasound signal emitted by the Falco Presence devices, as shown by the oscilloscope screen captures of the analog output signal. When the signal drops below 3 V the ultrasound signal is received.

5.5 Conclusion

This chapter introduces WELOC, an ultrasound-based localization system for localizing objects in a marina environment. By leveraging the existing infrastructure of commercial IoT devices equipped with ultrasound sensors, we are able to design a system that can accurately and efficiently localize objects on the pontoons. Our system features a scheduling scheme that allows us to determine which sensor triggered the ultrasound at any given time, without altering the main function of the Smart Parking system for boats. To evaluate the performance of our system, we design and test a mobile device using an off-the-shelf ultrasound sensor that is synchronized with each ultrasound trigger in the marina. Our lab tests show that the mobile device achieved a mean absolute error of 3.5 cm in ranging accuracy, with a maximum range of 10 m. Field testing in the marina, equipped with 471 presence sensors at each slip, demonstrate that our mobile device successfully detected the ultrasound signal on the pontoons. WELOC is a promising solution for localizing objects in a marina environment using existing infrastructure and off-the-shelf components, thus avoiding complex hardware design and additional installation costs. Integrating our system into existing Smart Parking systems for boats is simple and straightforward since it only requires a firmware or software update. Future work could involve further optimizing the system for improving the update rate and battery life of the mobile device, as well as exploring additional applications beyond marinas.

Chapter 6

Blip: Identifying Boats in a Smart Marina Environment

Parts of this chapter were published as part of the following article: *Blip: Identifying Boats in a Smart Marina Environment*. [Trifun Savić](#), Keoma Brun-Laguna, Thomas Watteyne. IEEE International Conference on Distributed Computing in Sensor Systems (**DCOSS-IoT**), Workshop on Intelligent Systems for the Internet of Things (**ISIoT**), Pafos, Cyprus, 19–21 June **2023**.

Key Takeaways: This chapter presents Blip, a system for boat identification in a smart marina environment. Blip combines the data from wireless IoT sensors already deployed to determine which boat is located at each slip. We develop the system using the Falco IoT solutions for smart marinas. Our system only uses the existing IoT infrastructure inside the marina, thus introducing no additional costs and hardware complexity. Blip combines data generated by the two types of sensors: Falco Presence deployed on pontoons for detecting a presence of a boat on a slip, and Falco Boat installed inside the boats for detecting events like intrusion, fire, tilt and shock. We validate our system on a historical dataset from 10-Aug-2021 to 30-Nov-2021, from the Sète marina in the South of France. The results show that the Blip system is 100 % accurate, successfully identifying 8 boats, 34 times upon their entry inside the marina.

6.1 Introduction

In Chapter 5, we showed how we can leverage the existing IoT infrastructure, present in a constrained marina environment, to enable localization. However, if we want to know which boat is located at which slip (boat identification) we need to deploy a mobile device on the boat, capable of receiving radio and ultrasound signal from the fixed infrastructure.

This chapter goes further and proposes Blip, a system for boat identification, that does not require the additional tracking device to be added to know at which slip certain boat is located. Blip combines the data collected from the presence sensors (installed on each slip to detect a presence of a boat) and the boat monitoring sensors (installed inside the boats' cabins to detect events such as intrusion, fire, tilt, shock), in order to estimate at which slip a boat is located. Blip combines two main information collected from these devices. First, the information from a presence sensor when a slip changes state from unoccupied to occupied, i.e. when a boat docks inside a marina. Second, from a boat monitoring sensor, a report containing the list of the presence sensors it can "hear" wirelessly (located close to the boat). Aside from the presence sensors' IDs, this report contains the information about the radio signal strength received from each presence sensor. This is called Receive Signal Strength Indicator (RSSI). The data used from the two sensors allow us to know exactly which boat occupies which slip inside the marina.

This chapter is organized as follows. Section 6.2 provides the problem statement and presents the contributions of the chapter. Section 6.3 presents the Blip algorithm for boat identification. Section 6.4 describes the dataset used for algorithm validation. Section 6.5 discusses the results. Section 6.6 concludes this chapter.

6.2 Problem Statement and Contributions

Aside from knowing if the certain slip is occupied, the marina wants to know which boat occupies the slip. This feature allows the marina to maximize slip occupancy and report in real-time where all the boats are inside the marina. Currently, boat identification is done manually in the marina; that is, teams of marina employee walk around the slips to write down which one is occupied, on a piece of paper. While commercial IoT devices (Falco Presence) exist for monitoring slip occupancy, they do not know which boat is on which slip, i.e. they do not perform boat identification. Automatic boat identification is highly beneficial to the marina managers. Having this information, they can know whether the boat is moored on a slip that is not indicated by the contract. Also, they are able to know if a small boat is moored on a big slip, and therefore have the maximum utilization of slips in the marina. Finally, marina managers can have the information about the number of times a boat entered/left the marina.

In previous work on boat identification inside a marina, Krpetic *et al.* [126] propose a berth occupancy and boat identification system using a ZigBee IoT network. The authors use ultrasonic sensors for the boat presence detection and ZigBee nodes installed inside boats as RFID tags. However, authors assume that the boat has docked at the right slip if a slip state changes to occupied and if the boat that should be at that slip appears inside the IoT network. This assumption is wrong when there is already a different boat at the slip, with the correct boat being already inside the marina on another slip and reporting its ID. Moreover, the authors do not report the validation of their system on a historical dataset from a marina. In our system, we use the presence sensors RSSI information collected by the boat monitoring device to determine the area of the marina where the boat is. Blip then combines this information with presence sensors changing

state from unoccupied to occupied in order to identify the boat. We also validate our approach on the historical dataset from Sète, a smart marina in the South of France. The results show that Blip is 100 % accurate, successfully identifying 8 boats in a 4 month period.

There are several localization and smart parking systems proposed in the literature, which we could deploy for our use case [42], [127]–[130]. However, we want to avoid introducing more complexity and additional costs to the existing IoT network, already deployed inside a smart marina environment. In addition, we also address the zero infrastructure dependency research challenge in constrained localization systems [124]. Usually, commercial localization and identification systems require heavy mains-powered infrastructure, which in most cases cannot carry any additional information like sensor readings or actuator commands. The proposed system does not require any mains-powered devices to serve as infrastructure, in order to enable boat identification. Blip uses the infrastructure of battery powered devices already deployed, capable of operating several years on batteries. Blip is a software update to an existing commercial IoT system.

Contributions of this chapter are threefold.

- We propose Blip, a system for boat identification in a smart marina environment. This system combines the data from the existing wireless, battery-powered, IoT devices to know which boat is at which slip. These devices are riveted under the pontoons for monitoring boat presence (Falco Presence) and installed inside the boats' cabins for boat monitoring (Falco Boat).
- The proposed system is designed completely in software/firmware and could be enabled just by updating the existing software.
- We validate the proposed system on the real-world dataset from Sète marina in the South of France. The data spans from 10-Aug-2021 to 30-Nov-2021, and contains all the data generated by all devices inside the Falco network. We show that Blip is 100 % accurate, successfully identifying 8 boats inside the marina.

6.3 Blip Algorithm

In order to implement Blip we use the experimental setup introduced in Section 3.2.2. Boat identification happens each time a boat enters a marina. For the algorithm to work, the marina needs Falco Presence sensors to be installed on pontoons, and a Falco Boat sensor inside a boat we want to identify upon entering the marina. We process the data from the sensors and as a result, the algorithm outputs a slip where the boat is located. As we already mentioned, the Falco IoT network is a time synchronized wireless sensor network, which is essential for the proposed system. Data generated by the Falco devices are timestamped, which allows us to easily combine the data from different sensors.

From the Falco Boat devices Blip uses the following data: health reports (hrs), join and lost events. The Falco Boat generates a health report every 22.5 min, when it is

operational inside the marina network. This packet contains the list of neighbor devices from the network, which it can wirelessly “hear”. For each of the discovered devices, the health report contains the MAC address of the neighbor device and the Received Signal Strength Indicator (RSSI) of the frame received from that device. From this data, we only need the information regarding the Falco Presence devices in the vicinity of a boat. Therefore, Blip filters all the health reports generated from the Falco Boat device, keeping only the health reports that correspond to discovered Falco Presence devices. The join and lost events are generated by the marina network each time a Falco Boat device connects/disconnects from the network. We use this information to determine whether a certain boat enters the marina. If the boat enters the marina, the algorithm runs all the steps to identify the boat upon mooring at its slip.

From Falco Presence devices we collect: the GPS locations of Falco Presence and the presence events. Each slip inside the marina correspond to one Falco Presence device. During the installation of the Falco Presence devices, their GPS coordinates were recorded. The presence events are generated by the Falco Presence device each time it detects a change in the occupied/unoccupied state of the slip. Blip algorithm looks for all Falco Presence devices inside the marina that change state from unoccupied to occupied in a given time window. It uses this information to determine when a boat has entered (or left) some particular slip.

Finally, we select the appropriate presence time window as an input to the algorithm, in which we observe the state of the presence sensor events. In the selected time window, Blip looks for the slips that changed state from unoccupied to occupied. When the boat enters a marina, it needs time until it moors at its slip. As the boat navigates through the marina, its Falco Boat device can join the network before it docks, resulting in a presence event *after* the join event. On the other hand, Falco Boat can also join the network after the boat docks, which causes the presence event changing from unoccupied to occupied *before* the network join event. We therefore center the presence events time window at the Falco Boat’s join event time. This means that the algorithm observes presence events half of the time window before and half of the time window after the join event time.

Algorithm 1 shows all the steps for the boat identification. The inputs of the algorithm are: health reports, join and lost events, presence events, slip locations and time window t . From join and lost events, we first check if the boat equipped with a Falco Boat device has entered the marina. If we find that a boat entered the marina, we take all presence events within a time window, centered at the join time of a Falco Boat device that entered marina. If there is only one Falco Presence that changed state to occupied we output the location of that sensor as a result. Otherwise, from the Falco Boat’s hrs, we select the discovered Falco Presence devices with the highest RSSI and assign its slip location (latitude and longitude) to the boat. If there are presence sensors that change state from unoccupied to occupied in the given time window, we extract the list and calculate the distance between each presence sensor location and the slip location obtained from hrs. We compute the distance using Haversine or the great circle distance [131]. The distance between the two sensors d is calculated as follows:

$$d = 2r \arcsin \cdot \sqrt{\sin^2 \left(\frac{(x1 - y1)}{2} \right) + \cos(x1) \cos(y1) \sin^2 \left(\frac{(x2 - y2)}{2} \right)} \quad (6.1)$$

where r is the radius of the Earth and $(x1, x2)$ and $(y1, y2)$ are the latitude and the longitude of the two presence sensors, respectively. The result of the Blip algorithm is a slip with smallest d .

Algorithm 1: Blip

Input: hrs, join, lost, presence event, slip, t

Output: slip

- 1 Look for a **join** event from Falco Boat
 - 2 Upon **join** check,
 - (I) **if** boat in **lost**, then boat entered marina.
 - (II) **else**, first **join**, go back to 1.
 - 3 Get **presence events** in $((\mathbf{join} - t/2) + (\mathbf{join} + t/2))$.
 - 4 Get every **slip** location from 3.
 - 5 **if** only 1 presence event **then** result \rightarrow **slip** location
 - 6 **else** from **hrs** get **slip** with $\max(RSSI)$.
 - 7 Calculate d between **slip** in 6 and each **slip** in 4.
 - 8 Result \rightarrow **slip** location from 4, where $\min(d)$
-

6.4 Dataset

We implement Blip in Python and validate it on historical dataset from the Sète marina in the South of France. The dataset spans from 10-Aug-2021 to 30-Nov-2021, and contains all the data generated by all devices inside the Falco network. This marina is entirely equipped with Falco Presence sensors, installed on each of the 471 slips. In addition to the presence sensors, there are 8 boats that have a Falco Boat device installed in their cabins. Blip identifies the boats as they arrive in the marina and dock at a certain slip.

In our dataset, we found 34 events for 8 boats entering the marina. For each of these events, our implementation computes the slip it believes the boat just moored at. We obtain the ground truth from the contract that each boat has with the marina. A contract contains the information regarding a slip assigned to a boat, and conformation from the marina crew the boat indeed moors there. The goal of our validation is to ensure our algorithm locates the boat at the slip where we know it has moored.

6.5 Results

Fig. 6.1 shows the number of successful boat identifications, depending on the time window in which we observe the state of Falco Presence sensors. With a narrow time window of 15 min, there are only 20 out of 34 successful boat identifications.

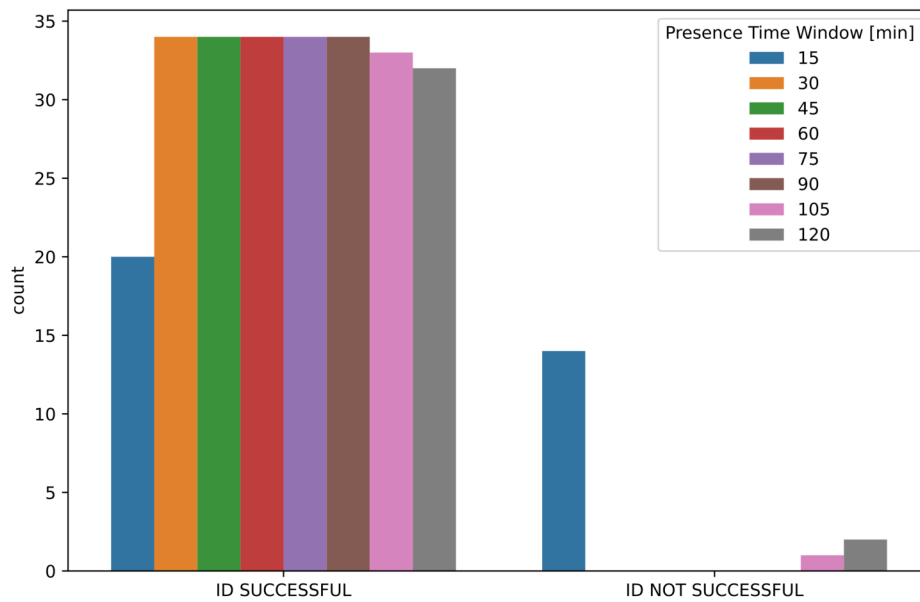


Figure 6.1: Number of successful boat identifications depending on different presence event time window. The ground truth was obtained from the marina crew confirmation regarding boats' locations and from the contract that each boat has with the marina.

This indicates that, in some cases, a boat docks before/after the join network time, outside of the selected time window. Therefore, we have 14 moorings without successful identification. On the other hand, if we select the time window that is too wide, we also have some unsuccessful identifications. In case of 105 and 120 min, there are 1 and 2 unsuccessful boat identifications, respectively. This is due to another presence event that happened on a slip located close to the slip where the boat is.

As our algorithm uses the RSSI readings from the presence sensors and assigns a boat to the slip with the highest RSSI, the algorithm reports an unsuccessful identification when two presence sensors are too close to each other. However, Blip ends up with two or more possible slips. Therefore, the algorithm is able to determine that this case occurred, and warn the marina, but it is then up to the marina to go on the pontoons and disambiguate.

As mentioned in Section 6.3, Falco Boat devices send a health report packet containing the MAC addresses and the RSSI readings of the discovered devices, every 22.5 minutes. Therefore, we select the presence event time window of 60 min. We look for a slip that changed state from unoccupied to occupied 30 min before/after Falco Boat joins the network. Using a 60 min presence event time window, the results show that Blip system is 100 % accurate, correctly identifying which boat is on which slip. Fig. 6.2 shows the

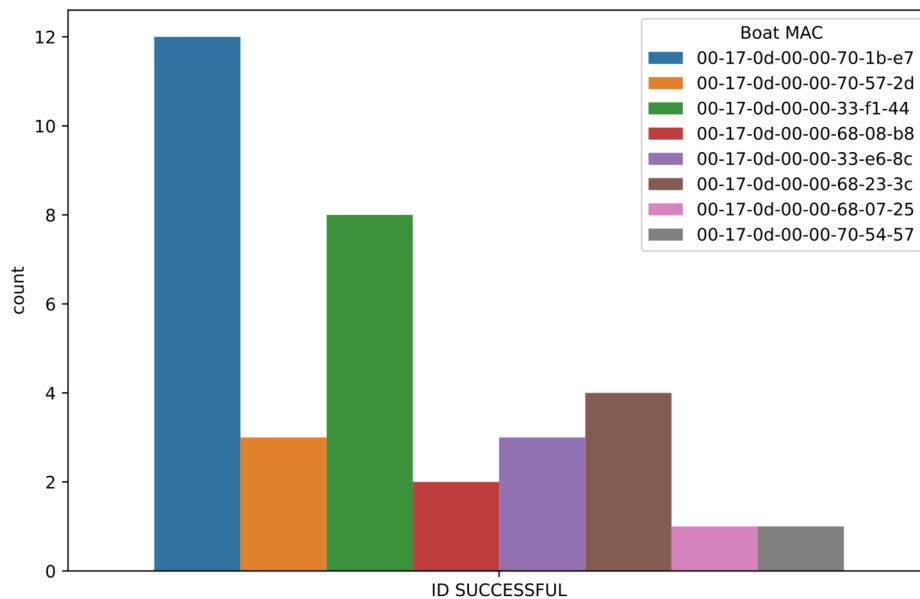


Figure 6.2: Boat identification using 60 min presence event time window.

number of successful identifications for 8 boats inside the Sète marina. Moreover, the number of successful boat identifications correspond to the number of times a certain boat left and entered the marina.

6.6 Conclusion

This chapter presents Blip, a system for boat identification in a smart marina environment. Blip combines the data from wireless IoT sensors already deployed to determine which boat is located on each slip. We develop the system using the Falco IoT solutions for smart marinas. Our system only uses the existing IoT infrastructure inside the marina, thus introducing no additional costs and hardware complexity. Blip combines data from two types of sensors: Falco Presence deployed on pontoons for detecting a presence of a boat on a slip, and Falco Boat installed inside the boats for detecting events like intrusion, fire, tilt and shock. We validate our system on a historical dataset from 10-Aug-2021 to 30-Nov-2021, from the Sète marina in the South of France. The results show that the Blip system is 100 % accurate, successfully identifying 8 boats, 34 times upon their entry inside the marina.

Chapter 7

RRDV: Robots Rendez-Vous Detection Using Time-Synchronized Ultrasonic Sensors

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Key Takeaways: This chapter proposes RRDV, a system for robot-to-robot encounter detection. We use a low-cost ultrasound sensor and time-synchronized mobile robots to detect when the two robots are facing one another. Ultrasound ranging is triggered by the control application on a computer. The application sends a ranging command to the gateway, which broadcasts it to the mobile robots over the radio. Robots synchronize their ultrasound trigger pin with the start of frame event and send back the notifications with measured distances using Time-Division Multiple Access (TDMA). The system then finds the encounters by searching for timestamps where the difference in distance reported by two robots is less than 1 cm. The current implementation achieves a 20 Hz ranging update rate. RRDV is validated experimentally using 5 mobile robots which are controlled by the users and moved randomly. We implement a Computer Vision (CV) algorithm for tracking mobile robots as they move and detect when they are facing one another. The results show 96.7% successfully detected robot encounters, when the duration of the encounter is more than 5 s.

7.1 Introduction

In Chapter 5, we presented a localization system that uses an existing infrastructure of ultrasound sensors. We demonstrated the use of an off-the-shelf ultrasound sensor for ranging between the anchors and the mobile device, which are primarily used for object detection. This chapter goes a step beyond and shows that the same ranging technique can be implemented for other use cases, such as robot encounter detection in a multi-robot system. For this purpose, we propose RRDV, a system for robot-to-robot detection using HC-SR04, an ultra low-cost ultrasound sensor. This type of sensor is ubiquitous in robotic systems, and used to measure the distance to obstacles. Without changing the hardware, we modify the function of this sensor so that, when a robot is in front of another robot, their sensors detect each other's ultrasonic pulse, allowing them to detect one another. The intuition is that, during an encounter, the distance reported by other robots' sensor is very similar. RRDV uses the wireless radio, equipping each robot to tightly synchronize them. Moreover, the robots use their radio to share their measured distances with a central entity, which analyses them and identifies the encounters between robot pairs.

We implement RRDV on a five-robot demonstrator. We use a computer as the control application we call "gateway". The gateway broadcasts a frame to all mobile robots signaling the start of a ranging cycle, using the BLE LR physical layer at 2.4 GHz. The robots arm a timer when they start receiving that frame; when that timer elapses, they activate the trigger pin of the ultrasound sensor. This causes all robots to send an ultrasonic pulse at the same time. When a robot collects the ultrasound measurements, it sends the range measurement in a wireless frame to the gateway using TDMA. The current implementation of the RRDV detects encounters at 20 Hz. To evaluate the performance of our demonstration system, we use CV software to track the robots and detect an encounter, using a high-resolution video of the experiment (Fig. 3.11). We use the results from the CV as our ground truth data and compare it with the RRDV encounter detection. We achieve 96.7% accuracy, when the duration of the encounter is more than 5 s.

This chapter is organized as follows. Section 6.2 defines the problem statement and presents the contributions of the chapter. Section 7.3 describes how we use the HC-SR04 ultrasound sensor. Section 7.4 presents RRDV. Section 7.5 shows the experimental results. Finally, Section 7.6 concludes this chapter.

7.2 Problem Statement and Contributions

In any multi-robot system, especially in swarm applications, knowing a position of the mobile robot relative to the infrastructure or to other robots is necessary [75]. Many constrained localization systems have been proposed in the literature, which, depending on the application requirements, enable robot positioning and tracking [124]. The information about the position is crucial for the robot's path planing. In distributed swarm systems, each robot needs to know where other robots are in order to avoid

mistaking the other robot for an obstacle. Moreover, robots need to be able to detect when they are close to the docking stations, in order to change/charge their batteries. As an addition to the localization system, it is equally important for robots to be able to detect one another, including to differentiate other robots from permanent obstacles.

Several ultrasound-based localization and ranging solutions are proposed in the literature [132]–[134]. Usually, researchers develop a custom ultrasound transmitter/receiver, time-synchronize them over radio or visible light, and measure ToA to calculate the distance. This approach could be used to detect an encounter. Nevertheless, designing a custom sensor is very costly. Moreover, custom sensors are hard to find and are not easy to integrate in a different multi-robot system. Instead, we use the HC-SR04, perhaps the most ubiquitous low-cost off-the-shelf ultrasound sensor, which typically costs less than 5 USD.

Given that the RRDV is completely implemented in firmware/software, using it simply means updating the firmware* on an existing robot. Mwaffo et al. [135] present a decentralized algorithm for control and state estimation to autonomously balance a group of robots in a circular formation. The algorithm works in two sequences: “pause”, where robots stop, collect and process the measurements from the sensors, and “go”, where robots accelerate to reach a desired spacing to its closest pursuant robot. The authors also use the same HC-SR04, and mount on a rotating platform on the robot, to measure the distance to other robots. They use the HC-SR04 in its normal way, treating a robot as an obstacle to detect. If they were using RRDV, the robots would explicitly detect an encounter.

Contributions of this chapter are threefold.

- One of the key contributions of this chapter lies in harnessing existing off-the-shelf ubiquitous sensors, which have already found widespread application in the field of robotics. These sensors, typically available for less than 5 USD, are commonly used in various robot applications as documented in existing literature. By utilizing this cost-effective sensor technology, we bypass the need for costly custom hardware design. This chapter demonstrates that the centimeter-level ranging accuracy achieved with these off-the-shelf sensors is more than sufficient for the successful detection of robot encounters. This finding provides valuable insights for researchers and practitioners seeking cost-effective solutions for robot-to-robot encounter detection.
- A significant contribution of this chapter is the complete implementation of RRDV in firmware and software. This software-centric approach allows for effortless integration into existing multi-robot systems. In cases where such systems already employ the same type of sensor (HC-SR04), adopting RRDV is as straightforward as updating the system’s firmware. This contribution facilitates the adoption of encounter detection capabilities without the need for complex hardware modifications or costly sensor replacements. It underscores the importance of

* As an online addition to this chapter, all the source code used is published under an open-source BSD licence at <https://github.com/DotBots/RRDV>

adaptable and software-driven solutions in advancing the field of multi-robot systems, promoting efficiency and ease of adoption.

- We perform the empirical evaluation of RRDV on a testbed consisting of five robots operated remotely by volunteers and driven randomly. Through real-world experimentation, we obtain an encounter detection accuracy of 96.7%, specifically achieved when robots are positioned facing each other for a minimum duration of 5 seconds. The achieved accuracy level has direct implications for real-world applications where robots must closely interact and coordinate their movements, emphasizing the significance of this research in advancing the science of robotics and automation.

7.3 Detecting Encounters Using the HC-SR04

RRDV identifies pairs of mobile robots that are facing one another. We call these “encounters”. RRDV does so (re-)using the off-the-shelf HC-SR04 already present on many robots. As shown in Fig. 3.9, the HC-SR04 has two ultrasound transducers: one for transmitting an ultrasonic pulse, one for receiving it. In its normal operation, that pulse bounces off an obstacle in front of the sensor; the HC-SR04 uses the speed of sound to turn that round-trip time into distance.

The key is that RRDV tightly synchronizes the robots using wireless. This allows the robots to trigger the transmission of their ultrasonic pulse at exactly the same time. Most of the time, this makes no difference, each robot measures the distance to an obstacle in front of it. But if a pair of robots face one another, the RRDV sensor on one robot receives the pulse from the other robot, rather than its pulse that has bounced off an obstacle. Because the two robots have emitted their pulse at the same time, they both measure the same distance. That is, in a swarm of robots, if two robots measure the same distance, there is a high likelihood they are facing one another. If the robots are measuring the same distance to an obstacle, they will detect a false encounter. We can easily solve this by having robots move together, and verify if the encounter detection is still valid.

Fig. 7.1 illustrates the operation of the HC-SR04. We call l_1 and l_2 the output of sensor 1 and sensor 2, respectively. If the sensors are facing an obstacle, the distance measurement of the sensors correspond to $l_1 = d_1$ and $l_2 = d_2$ (Fig. 7.1 a). If the sensors are facing one another, $l_1 = l_2 = l$ and the distance between the two sensors is calculated as $d = 2l$, assuming that the sensors are time synchronized, and we detect an encounter (Fig. 7.1 b). Due to the inaccuracy of the sensors and the imperfection of the time synchronization, the measured distances l_1 and l_2 will be slightly different. Therefore, in our implementation, if the difference between l_1 and l_2 is below a threshold Δl , we consider they are the same.

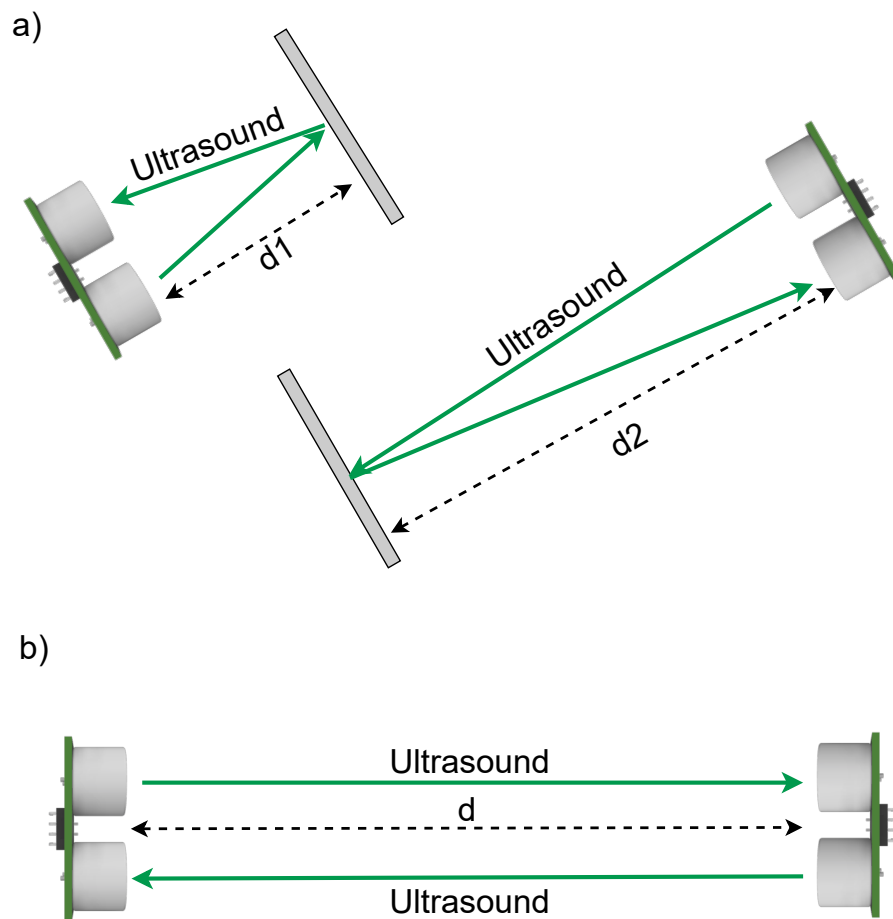


Figure 7.1: Ultrasound sensors operation in the RRDV system. Sensors are time-synchronized. *a)* Normal operation, the HC-SR04 measures the distance to some obstacle. *b)* Encounter detection, the HC-SR04 pair measure the distance to one another and check if the difference between the two sensor outputs is less than a threshold Δl .

7.4 RRDV

RRDV has three core elements (Fig. 7.2): control application, gateway, robots. We detail each in the next paragraphs.

RRDV is a centralized system, managed by the **control application**, running on a computer. We implement the control application in Python. The application communicates with the gateway over Universal Asynchronous Receiver-Transmitter (UART), using High-Level Data Link Control HDLC framing. One ultrasound ranging cycle starts when the application sends a 32-bit bitmask to the gateway. Each bit in the command corresponds to the unique identifier (ID) of a robot. If a bit in the bitmask is set, the corresponding robot triggers the ultrasound measurement and sends back the notification with measured distance. After issuing a command, the application waits for the incoming serial notification frames from the gateway. These frames contain the recorded distance measurements and robot IDs respectively. When the application receives all the frames, it saves them to a Comma-Separated Values (CSV) file. All robots range at the same time. One ultrasound ranging cycle takes 50 ms; RRDV has a 20 Hz update rate.

Fig. 7.3 is the chronogram of the RRDV state machine. Both gateway and robot use a single timer peripheral to implement RRDV. We reuse the BLE LR physical layer at 2.4 GHz as a radio link between the mobile robots and the gateway. When the gateway receives an HDLC frame from the control application, it parses the data and prepares a radio frame. The frame contains the gateway ID and 32-bit bitmask. The gateway broadcasts that frame to all robots over its radio, then waits to receive frames from the robots. It waits for a duration that depends on the number of robots and how those are scheduled in the TDMA communication scheme (described in Fig. 7.4). After parsing the frames it received from the robots, the gateway sends that information over its serial port to the control application.

Robots receive frames from the gateway, and use that as a trigger for their HC-SR04 sensors. A robot starts by listening for frames from the gateway. On reception, it starts a timer and configures it to trigger the HC-SR04 when it expires. It then inspects the received frame, and cancels the timer if its bit is *not* set in the bitmask contained in the frame. This use of the timer allows the HC-SR04 to be triggered at a perfectly deterministic time, without any jitter introduced by the speed of execution of the CPU. After it has triggered the HC-SR04, it captures the output of the “echo” pin, which encodes the distance measured in its pulse width. The robot then waits for its right TDMA timeslot, and sends the measured duration to the gateway over the radio.

7.5 Results

We implement and test RRDV using the hardware and experimental setup shown in Section 3.2.3. This section details the analysis of the data, including fine-tuning of the encounter detection routing running on the computer, and the resulting performance of RRDV. We evaluate the performance in terms of success (both video and RRDV detect

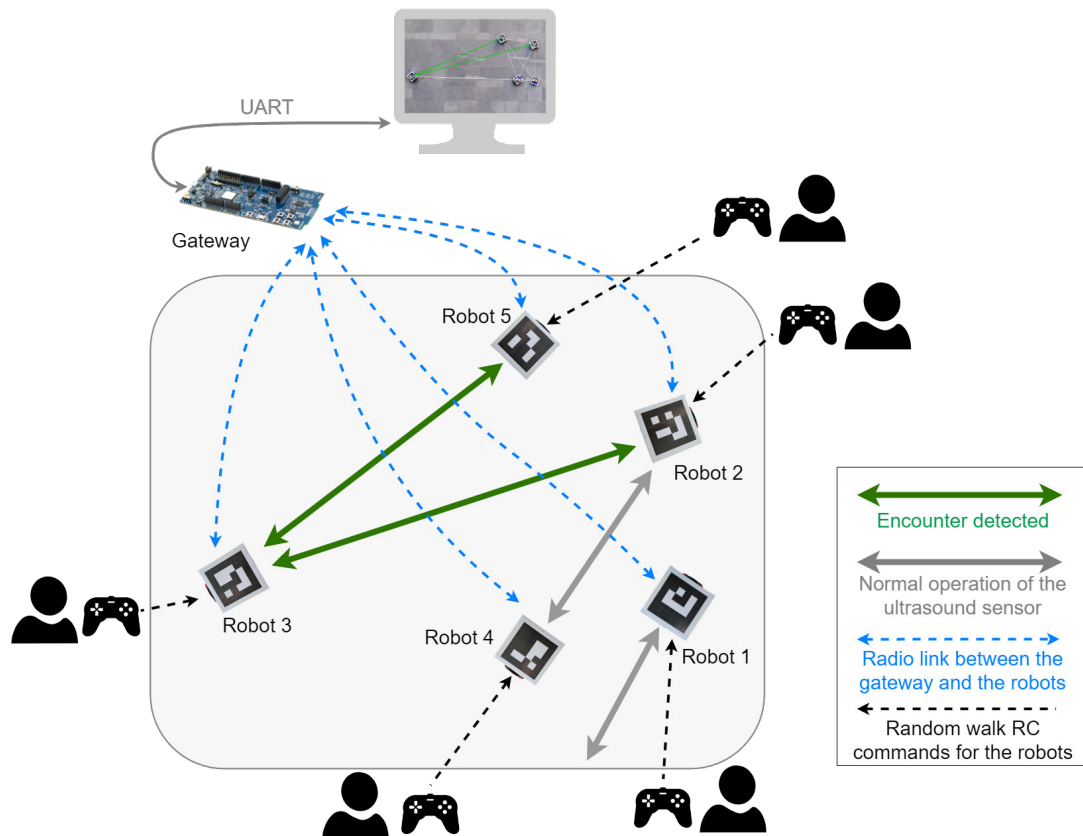


Figure 7.2: Diagram of the proposed system demonstrating encounter detection in the experimental evaluation.

Table 7.1: A threshold of 1.0 cm results in the highest success.

threshold Δl	success	miss	false positive
0.5 cm	53.90%	46.10%	5.00%
1.0 cm	72.30%	27.66%	12.82%
1.5 cm	71.63%	28.37%	17.89%
2.0 cm	69.50%	30.50%	20.33%
2.5 cm	65.96%	34.04%	23.77%

an encounter), miss (the video indicates there is an encounter, but RRDV misses it) and false positive (RRDV detects an encounter, but the video shows it didn't happen). The entire experiment takes 12.5 min, where each robot sends a packet with measured distance every 50 ms. The robots move randomly.

Based on the speed of the cars, we know that an encounter lasts for at least 1 s. We also know that two successive encounters between the same two cars cannot happen within 3 s. We hence start our analysis by cleaning up the data, removing spurious measurements based on these two timing. These measurements can be caused by dropped ultrasonic pulses.

We then consider the value of threshold Δl , below which distance measurements are considered the same. This value allows for a trade-off between success and false positive. We compute success and false positives for five value of Δl , see Table 7.1. A threshold of 1.0 cm results in the highest success. We use that value for the remainder of this section.

Fig. 7.5 is a timeline of the different encounters. It shows 10 sub-plots, one of each robot pair (there are 5 robots, so $\frac{5 \cdot (5-1)}{2} = 10$ undirected pairs of robots). In each, the lines at the top represent the periods over which the camera witnesses an encounter; the dots at the bottom represent encounters as detected by RRDV. When both camera and RRDV detect an encounter at the same time, that's a success. A camera detection alone is a miss. A RRDV detection alone is a false positive. The performance of RRDV consists in classifying the events as success, miss and false positive, and counting the number of encounters of each category.

Fig. 7.6 shows the results for different distances between robots and different encounter duration. The top plot show that, the closer the robots, the better RRDV works and that, with this setup, RRDV is best used for robots are less than 2 m apart. Similarly, the bottom plot shows that, the longer robots stay facing one another, the better RRDV works (i.e. the higher the likelihood it will successfully detect an encounter). If the robots face one another for more than 5 s, the success rate is 96.7%.

In this implementation, RRDV offers an encounter detection frequency of 20 Hz. This depends on the number of robots. To allow for fast update rates when there is a large number of robots, the control application could be optimized by having it dynamically modify the bitmap in the command frame. This way, pairs of robots that are likely to be facing one another could be ranging more often, while others, which are known for

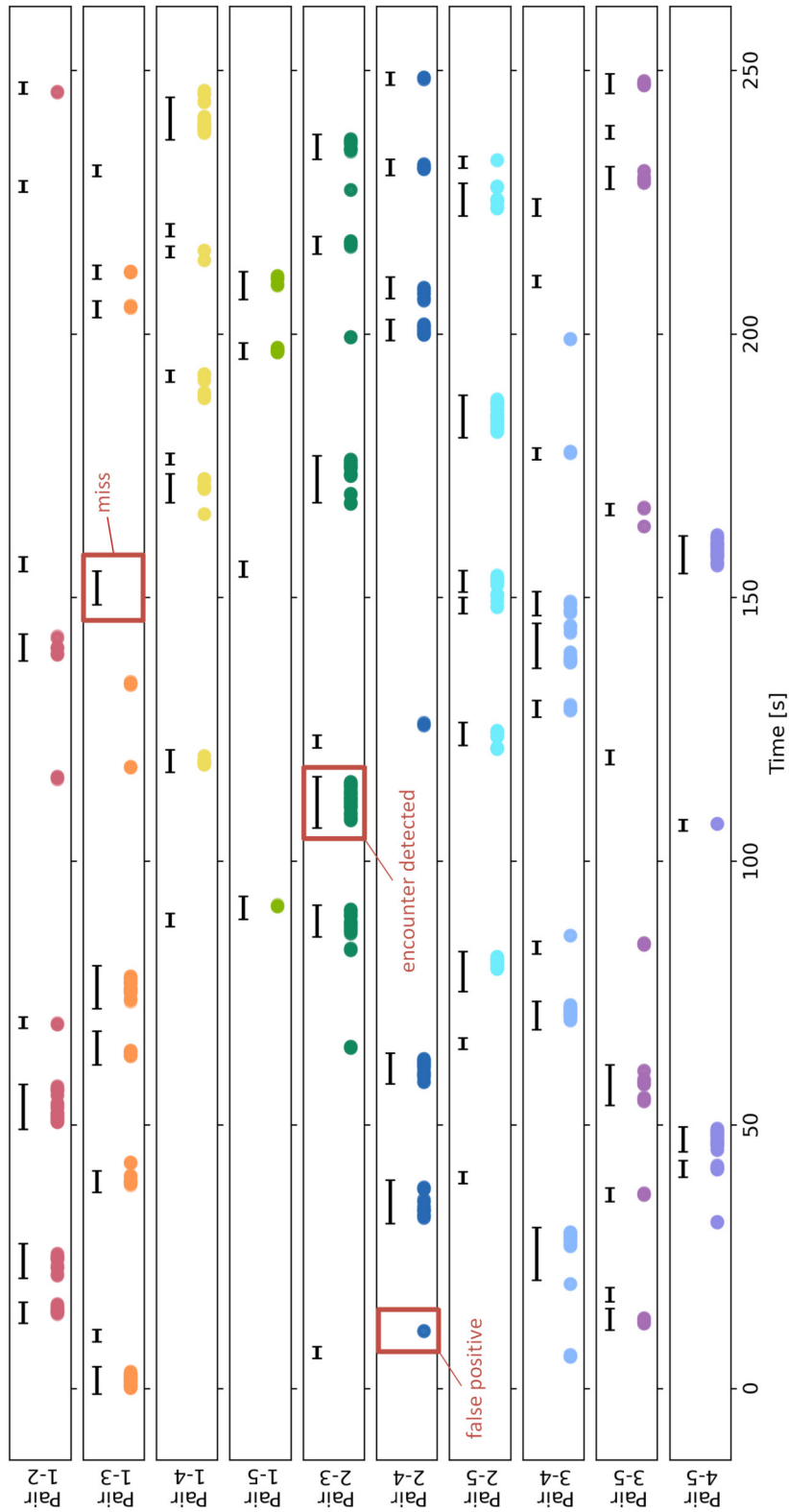


Figure 7.5: Timeline of the encounters, as detected by the camera and RRDV. There is a subplot for each robot pair. A line at the top of a subplot represents the periods over which the camera witnesses an encounter. A dot at the bottom of a subplot represents encounters as detected by RRDV.

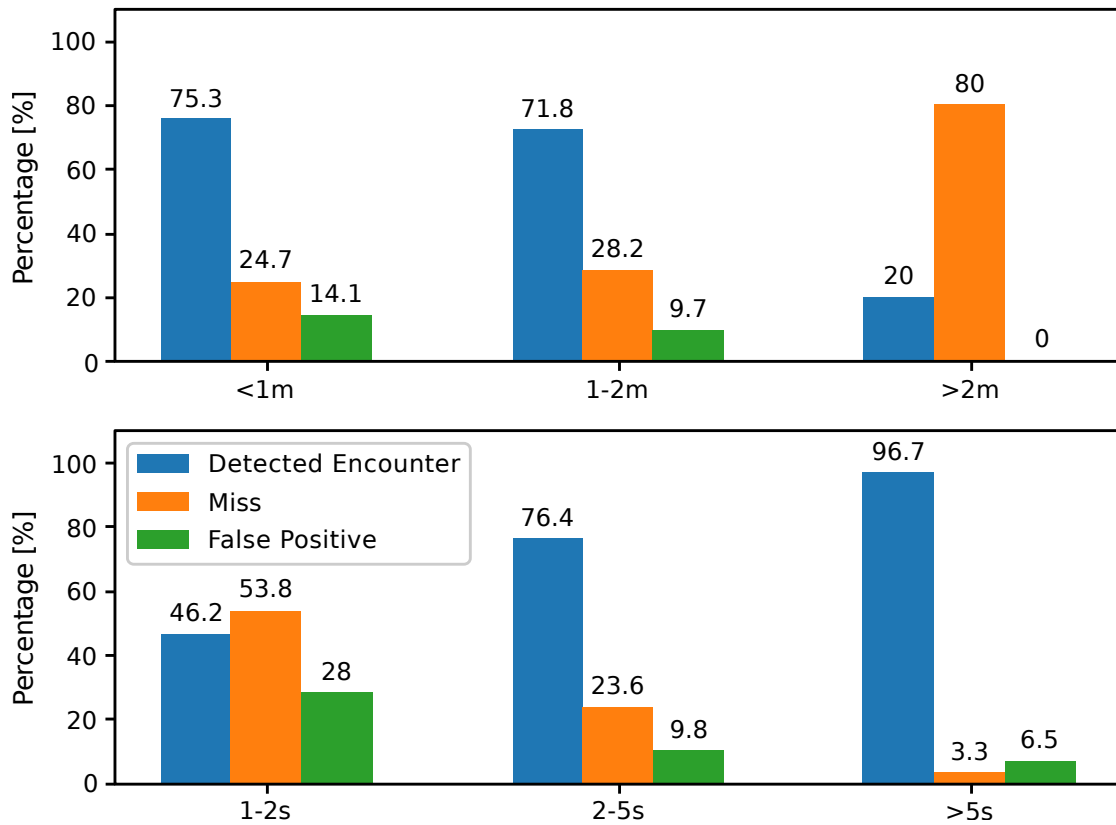


Figure 7.6: Encounter detection accuracy at different distances between mobile robots (top) and different duration of the encounters (bottom). To evaluate the performance we count the following events: success (both video and RRDV detect an encounter), miss (the video indicates there is an encounter, but RRDV misses it) and false positive (RRDV detects an encounter, but the video shows it didn't happen).

example to be in different areas of the deployment, would not be.

7.6 Conclusion

This chapter introduces RRDV, that allows robots to detect they are facing one another in a multi-robot systems. What makes RRDV powerful is that it reuses ultrasonic sensors such as HC-SR04 already present on many robots; RRDV can be seen as a software update. Robots are time-synchronized and use that timing information to trigger the ultrasonic pulses of the sensors. The system detects an encounter when the two robots involved report the same distance. We validate our system by equipping five Radio Controlled (RC) cars. We implement a CV algorithm to track the positions of those cars, information we use as ground truth in our analysis. The results show that RRDV has an accuracy of 96.7%, when the robots are facing each other for more than 5 s.

Chapter 8

Conclusions and Future Work

This chapter concludes this manuscript by summarizing the work and listing the main contributions of this thesis (Section 8.2), and discussing the avenues for future work that this thesis has opened (Section 8.2).

8.1 Summary and Contributions

This thesis contributes to the expanding research field of localization and IoT by addressing the challenges of developing accurate and low-power localization systems in constrained environments. Unlike existing solutions that require the prior deployment of fixed infrastructure, known as “anchors”, inside the IoT network, our approach does not rely on such infrastructure. For our first use case, smart marinas, we propose a novel method that utilizes existing hardware and sensors to enable accurate localization without the need for additional fixed anchors. This innovation has significant implications for the development of cost-effective and energy-efficient localization systems in various constrained environments. For our second use case, we design a system for mobile robots’ encounter detection in a swarm. Using a hands-on approach, we design the system using off-the-shelf low-cost hardware, and demonstrate experimentally this effective solution, which is complementary to a localization system. Proposed system opened up many avenues for future work, which we discuss in the last section of this chapter.

We organize this manuscript in seven core chapters, including four with technical contributions.

Chapter 1 provides an introduction of the topic of this thesis. We describe our main driving use cases: localization in a smart marina environment, indoor localization of mobile robots. We cover the basics of IoT technology and its use in real-world scenarios. Then we discuss localization fundamentals: techniques, technologies, and architecture types. We first highlight the main localization techniques and how to apply them. Then, we list the main localization technologies used in the academic research and commercial market today, and the typical architecture types in localization systems. We conclude the introduction by outlining the organization of this manuscript.

In Chapter 2, we conduct a survey of recent academic research related to the indoor

localization. Throughout the chapter, we focus on the specific use case of localizing miniature wireless swarm robot, DotBot. To guide our survey, we define a taxonomy and classify academic research based on five criteria: LOS requirement, accuracy, update rate, battery life, and cost. Our analysis leads us to identify and discuss the five most important open research challenges, including lightweight filtering algorithms, zero infrastructure dependency, low-power operation, security, and standardization. In summary, Chapter 2 provides valuable insights into the academic research landscape related to my thesis and lists the key contributions of my work.

In Chapter 3, we provide a detailed description of the methodology used to develop and evaluate the proposed solutions in this thesis. We argue that the hands-on approach, which involves real-world experimentation, is challenging yet complementary to analysis and simulation in low-power wireless systems. We first present the tools and setup used to test the commercial solutions for AoA estimation and UWB ranging. Then, we provide a detailed description of the IoT network and devices inside Sète marina that we used to develop WELOC and Blip. Finally, we describe the experimental setup for RRDV. Our methodology ensures that the proposed solutions are thoroughly evaluated and validated, and enabled the development of the Minimum Viable Product (MVP) for each solution.

In Chapter 4, we present a series of hands-on experiments that we conducted to evaluate the performance of popular RF-based technologies used in RTLS systems today. Specifically, we conducted experiments with commercial products based on Bluetooth AoA and UWB TWR. We use Texas Instruments and Nordic Semiconductor evaluation kits for AoA estimation, as well as Decawave UWB evaluation boards for UWB TWR. By using the provided equipment as-is, we gain first-hand insights into various constraints and limitations of these technologies. The results obtained from these experiments allow us to develop an intuition for the accuracy of angle and ranging estimations of the tested commercial products.

In Chapter 5, we propose a novel ultrasound-based localization system called WELOC, which is specifically designed for localizing objects in a marina environment. We leverage the infrastructure of already-installed commercial IoT devices, which are fixed at each slip on the pontoons and are used for boat presence monitoring. These devices are equipped with an ultrasound sensor, have known GPS positions, and form a wireless, time-synchronized mesh network around the gateway. To avoid interfering with the primary function of the smart parking system for boats, we propose a scheme to schedule when each ultrasound sensor is triggered. We design a mobile device using an off-the-shelf ultrasound sensor that is compatible with those already present in marinas. We synchronize the device with each ultrasound trigger in the marina and collect timestamped distance measurements, which are then used to compute the location of the mobile device using trilateration. We conduct laboratory tests to evaluate the ranging accuracy of the mobile device, achieving a mean absolute error of 3.5 cm with a maximum range of 10 m. We also perform field testing for the ultrasound signal detection inside the marina. Our results show that the mobile device successfully detects the ultrasound signal on the pontoons, validating the feasibility of our proposed solution.

Chapter 6 presents Blip, a boat identification system that leverages existing wireless

IoT sensors in a smart marina environment. Blip integrates data from two types of sensors: Falco Presence, which detects the presence of a boat on a slip, and Falco Boat, which detects various boat events such as intrusion, fire, shock. By combining the data generated by these devices, we develop a cost-effective and low-complexity system that identifies boats without requiring additional hardware. We evaluate Blip on a historical dataset collected from the Sète marina in the South of France from beginning of August to the end of November 2021. Our system achieves 100% accuracy, correctly identifying 8 boats, equipped with Falco Boat device, that entered the marina 34 times during this period.

Chapter 7 presents RRDV, a robot-to-robot encounter detection system that uses a low-cost ultrasound sensor and time-synchronized mobile robots. Ultrasound ranging is triggered by a control application on a computer, which sends a ranging command to the gateway that broadcasts it to the mobile robots over the radio. Robots synchronize their ultrasound trigger pin with the start of the frame event and send back the notifications with measured distances using TDMA. RRDV finds the events when the difference between measured distance of any two robots is less than a certain threshold, and reports an encounter. The current implementation achieves a 20 Hz ranging update rate. The system is validated experimentally using 5 mobile robots. We implement a Computer Vision (CV) algorithm for tracking mobile robots as they move and detect when they are facing each other, which we use as our ground truth. The results show that 96.7% encounters were successfully detected when the duration of the encounter was more than 5 s.

In summary, the main contributions of this thesis are as follows.

1. As our research is centered around the domains of IoT and low-power wireless, we aim to investigate the suitability of RF-based technologies for RTLS. In our use cases, IoT devices and mobile robots communicate wirelessly via radio, which can be leveraged for localization purposes. Recently, Bluetooth Angle of Arrival (AoA) and Ultra-Wideband (UWB) ranging technologies have gained traction, and we study their potential for RTLS applications. Our experiments demonstrate the accuracy of these technologies as provided by the manufacturer. Thus, presenting first-hand the constraints these technologies have.
2. Although indoor localization solutions surveyed in Section 2.3 show promising results, they suffer from a significant drawback: they require the deployment of fixed anchors that form an infrastructure and consume too much power to be powered by batteries. To address the research challenges identified in Section 2.4, we propose a localization system called WELOC that utilizes existing boat presence detection sensors in marinas as fixed infrastructure. All devices in the system use standardized and secure protocols for communication, and are all battery-powered. Unlike the RF-based commercial products we tested in Chapter 4, WELOC is designed to be battery-powered and does not require the installation of additional fixed anchors. By utilizing the existing IoT network inside the marina, which is time-synchronized over the radio, we schedule each presence sensor's ultrasound

transmission at specific times. Additionally, we design a mobile device using off-the-shelf components capable of receiving/transmitting both ultrasound and radio signals. We achieve 3.5 cm mean absolute ranging error and maximum range of 10 m in laboratory testing, assuming perfect synchronization. We demonstrate the ultrasound detection capabilities of WELOC in a real-life marina in the South of France.

3. By leveraging information from existing IoT devices installed on pontoons and boats, we can enable boat identification in marinas. Although the previously proposed WELOC system can provide identification of boats, it requires a dedicated tracking device to be installed. To address this limitation, in regards to know which boat occupies which slip, we propose Blip, a software/firmware-based system for boat identification in marinas. Blip utilizes boat monitoring sensors already installed in the boat's cabin, as well as information from the fixed infrastructure of presence sensors, to identify boats on slips. We demonstrate the accuracy of the system by successfully identifying boats in the marina using real-world datasets, achieving 100% accuracy.
4. Aside from localization in a marina environment the research conducted during this thesis also has applications in other domains, such as multi-robot systems. To address the topic of collision detection in a swarm, we propose RRDV, a system for detecting robot-to-robot encounters in multi-robot systems. This ultrasound-based system builds upon techniques previously used in WELOC and can complement a localization system. By tightly synchronizing the triggering of low-cost, ubiquitous ultrasound sensors mounted on mobile robots, we can detect when two robots are facing each other in a swarm. The system achieves 96.7% accuracy when the robots are in front of each other for more than 5 s. The main advantage of RRDV is that it uses off-the-shelf, ubiquitous hardware and can be implemented in existing robot systems as a software update, provided they use the same ultrasound sensor for measuring the distance to an object in front of the robot.

8.2 Avenues for Future Work

This work opens up several avenues for future work. Although WELOC (presented in Chapter 5) meets the application requirements described in Section 5.3, there are limitations of the current system that could be improved in the future. Section 8.2.1 highlights the major limitations and possible optimization approaches for WELOC. Section 8.2.2 highlights four main applications that could benefit from RRDV (presented in Chapter 7). These include: collision avoidance, mapping, docking stations for robots, and security.

8.2.1 WELOC 2.0

There are many sound-based localization systems proposed in the literature, offering cm-level localization accuracy [124]. Apart from the academic research, state-of-the-art commercial solutions offer cm-level asset tracking accuracy, combining technologies like ultrasound and radio [38]. In order to obtain this level of accuracy sound-based systems require Line of Sight (LoS). WELOC relies on the ultrasound multi-path signals. Falco Presence device has a direct LoS with the boat it is monitoring, but the mobile device located on the pontoon is, in most cases, receiving the reflected ultrasound signal. This increases the error in the mobile device's position estimation. However, in this paper we are not aiming for the cm-level accuracy of the sound-based systems, as the accuracy requirement is a localization error of less than 1 m. The dense deployment of Falco Presence devices inside the marina minimizes the localization error caused by the reflected ultrasound signal. Moreover, when a boat is located at the slip, the LoS distance between a Falco Presence device and a boat is less than 20 cm. In the case of an absence of a boat, the mobile device can have direct LoS with the Falco Presence device, allowing a cm-level ranging accuracy.

In most sound-based localization systems available in literature, the anchors are installed above the mobile device, in order to minimize the number of anchors needed and allow a better ultrasound signal coverage. As we show in Section 3.2.2, Falco Presence devices are riveted under the pontoons, at each slip inside the marina. Using these devices as anchors in a localization system is not ideal, due to their location under the floor level. However, we could improve the coverage of signal by equipping other IoT devices inside the network with ultrasound sensor. In the Falco IoT network, apart from the sensing devices, we install wireless repeaters above the pontoons in the marina, each located approximately 10 m from each other. These devices serve as relays inside the network, providing good wireless communication links between the IoT devices and the gateway. We could improve ultrasound signal coverage in WELOC by equipping these repeaters with one or more ultrasound sensors. This would also improve the accuracy of the system, as the repeaters are located on the poles above the pontoons, with the direct LoS with the mobile device.

In the current WELOC implementation, a mobile device needs to activate its receiver each time a Falco Presence device triggers its ultrasound sensor. In the real-life use case shown in Section 3.2.2, there are 471 Falco Presence devices, and one ultrasound ranging cycle lasts for 15.1 s. For most of the time the mobile device is performing ranging without receiving ultrasound signal, because it is far away from most of the Falco Presence devices in the marina. The mobile device is located on a pontoon with only a few fixed devices in its proximity. Therefore, optimizations could be made to improve the localization update rate and battery life of a mobile device. In WELOC, we could use RSSI to determine at which pontoon or part of it the mobile device is located. The mobile device has a wireless radio, time-synchronized with the IoT network, and it is capable of measuring the RSSI of its neighbor devices (Falco Presence). This way we could first have a rough location estimation of the mobile device, for example a pontoon at which it is located, and then schedule the ultrasound transmissions of its neighboring Falco Presence devices.

8.2.2 Applications Benefiting from RRDV

Existing multi-robot systems that use both radio communication and an ultrasound sensor could easily take advantage of RRDV without requiring any hardware update. This section lists four applications that could benefit from RRDV.

Collision avoidance. When many robots move in an area to perform tasks, there is a high likelihood they will bump into one another, even when complex algorithms are used for controlling their movement [136]. RRDV can be used in the navigation routines on a robot to differentiate between static obstacles and moving robots, resulting in more efficient swarm movements.

Mapping. Swarm of robots are used to collectively carry out exploration and mapping of unknown areas [75]. These robots can be updated with RRDV to avoid mistaking another robot for an obstacle. Since RRDV does not alter a robot's ability to range, the sensor on a robot would continue to be used in its mapping routines.

Docking stations. When robots need to charge/change their batteries, they typically need to dock [137]. Detecting when a robot is in front of the docking station is necessary for assisting the robot to stop at the right place. RRDV can be used to recognize when a robot is near the docking station. Using RRDV, a robot can position itself at the right angle and stop safely at the docking station. Here, both robots and docking stations are equipped with RRDV.

Security. Using RRDV, a robot can recognize that it is close to another robot. They can use this to trigger the exchange of messages over the radio and establish a secure communication link. RRDV can also be used for physical layer security: two robots can encode their security keys by modulating the distance measurement (driving back-and-forth) removing the opportunity for an eavesdropper to hear the keys.

Chapter 9

Publications

Journal Articles:

1. *Constrained Localization: a Survey*.
Trifun Savić, Xavier Vilajosana, Thomas Watteyne. **IEEE Access**, volume 10: 49297-49321 **2022**.
2. *Lighthouse Localization of Miniature Wireless Robots*.
Said Alvarado-Marin, Cristobal Huidobro-Marin, Martina Balbi, Trifun Savić, Thomas Watteyne, Filip Maksimovic. **IEEE Robotics and Automation Letters**, to appear in **2023**, *under review*.

Conference Papers:

1. *RRDV: Robots Rendez-Vous Detection Using Time-Synchronized Ultrasonic Sensors*.
Trifun Savić, Said Alvarado-Marin, Filip Maksimovic, Thomas Watteyne. **IEEE International Conference on Robotics, Automation and Artificial Intelligence (RAAI)**, Singapore 9–11 December **2022**.
2. *Blip: Identifying Boats in a Smart Marina Environment*.
Trifun Savić, Keoma Brun-Laguna, Thomas Watteyne. **IEEE International Conference on Distributed Computing in Sensor Systems (DCOSS-IoT), Workshop on Intelligent Systems for the Internet of Things (ISIoT)**, Pafos, Cyprus, 19–21 June **2023**.
3. *WELOC: Localization Equipment in Marinas using Ultrasound*.
Trifun Savić, Keoma Brun-Laguna, Thomas Watteyne. **Special session on Navigating the Opportunities and Challenges in Maritime IoT, IEEE World Forum on Internet of Things (WF-IoT)**, Aveiro, Portugal, 12–27 October **2023**, *accepted*.

Patents:

1. *Système de Localisation de Dispositif Mobile pour Port de Plaisance.*
Trifun Savić, Keoma Brun-Laguna. patent submitted. n° dépôt : FR2203787.
2. *Localisation et Identification de Bateaux au Sein d'un Port de Plaisance.*
Trifun Savić, Keoma Brun-Laguna. patent submitted. n° dépôt : FR2302216.

Entrepreneurship:

1. I am the lead hardware designer of various low-power wireless products for smart marinas, commercialized by the industry leader **Wattson Elements - Falco** (<https://wefalco.com>).

Open-source contributions:

1. I wrote drivers for interfacing with the radio and sensors for the **DotBot** project (<https://github.com/DotBots/DotBot-firmware>).
2. I designed a PCB for controlling an autonomous sailing boat for the **SailBot** project (<https://github.com/DotBots/SailBot-PCB>).

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