DEVELOPMENT OF A NOVEL RANGE AND BEARING SYSTEM FOR ROBOT SWARMS

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ABSTRACT

DEVELOPMENT OF A NOVEL RANGE AND BEARING SYSTEM FOR ROBOT SWARMS

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This thesis presents the design and evaluation of two novel range and bearing (RnB) systems specifically designed for swarm robots, addressing the challenges inherent to robotic interaction and navigation. Two different RnB are introduced: the first one has a pioneering range and bearing system equipped with twelve time-of-flight sensors, while the second one integrates eight advanced sensors with multi-zone distance measurement capability. A notable contribution is the robot detection algorithm that enables these systems to distinguish neighboring robots from other obstacles and accurately measure their distances using onboard microcontrollers. Furthermore, the use of Multi-Target Tracker (MTT) increased the utility of these systems by estimating the current pose and velocity of detected robots. Each system is designed to span 55 millimeters and weigh almost 10 grams, making it suitable for micro aerial vehicles and mobile robot swarms. Experiments were conducted to analyze range measurement, robot detection, and multi-target tracker performance. Finally, flocking algorithms were tested with MAV swarms and ground robot swarms to provide proof of concept of the system.
Keywords: swarm robotics, range and bearing sensing, relative localization, micro-aerial vehicle swarm
ÖZ

ROBOT SÜRÜLERİ İÇİN ÖZGÜN UZAKLIK VE KERTERİZ SİSTEMİNİN GELİŞTİRİLMESİ

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Bu tez, robotik etkileşim ve navigasyonun doğasında var olan zorlukları ele alarak, özellikle sürü robotlar için tasarlanmış özgün uzaklık ve kerteriz sistemlerinin tasarımı ve analizini içermektedir. Tez kapsamında iki farklı sistem tanıtılmaktadır. Bunlardan ilk, on iki uçuş süresiyle ölçüm yapan mesafe sensörleriyle donatılmış uzaklık ve kerteriz sistemine sahipken, ikinci tasarım çoklu ölçüm yeteneğine sahip sekiz mesafe sensörünün entegresiyle oluşturulmuştur. Bu tezin en önemli kazanımı ise bu sistemlerin komşu robotları diğer objelere ve engellerden ayrımsız olacak şekilde ürettiği robot algılama algoritmalarıdır. Tez kapsamında geliştirilen Çoklu Hedef İzleyici (MTT), tespit edilen robotların mevcut konumlarının ve hızlarının tahmin edilmesini sağlar. Özellikle kompakt tasarlanan bu iki sistem sadece 60mm çapa ve 12 gram ağırlığa sahiptir. Bu özellikleri ile iç ortam kullanımındaki mikro hava araçları ve küçük robotlar için uygunlardır. Bu sistemlerin uzaklık ölçümü ve robot algılama performanslarını test etmek amacıyla bir dizi deneyler yapılmıştır. Sistemin sürü robotlar ile çalışma konseptine uygulanıp uygulanıp kavranma amacıyla sürü robot al-
goritmalaryla sistemler test edilmiştir.

Anahtar Kelimeler: sürü robotik, uzaklık ve kengeriz algılaması, göreceli konumlanma, küçük hava araçları sürüsü
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<td>FoV</td>
<td>Field of View</td>
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<td>ToF</td>
<td>Time of Flight</td>
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<td>RnB</td>
<td>Range and Bearing System</td>
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<td>CAD</td>
<td>Computer Aided Design</td>
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<td>IR</td>
<td>Infrared</td>
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<tr>
<td>I2C</td>
<td>Inter Integrated Circuit</td>
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<tr>
<td>MAV</td>
<td>Micro Aerial Vehicle</td>
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<tr>
<td>MCU</td>
<td>Micro Controller Unit</td>
</tr>
<tr>
<td>PCB</td>
<td>Printed Circuit Board</td>
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<td>ROS</td>
<td>Robot Operating System</td>
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<td>RPi</td>
<td>Raspberry Pi</td>
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<tr>
<td>SPI</td>
<td>Serial Peripheral Interface</td>
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<tr>
<td>UART</td>
<td>Universal Asynchronous Receiver Transmitter</td>
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<tr>
<td>WiFi</td>
<td>Wireless Fidelity</td>
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Swarm robotics, a field inspired by the collective behaviors of social animals, aims to emulate the complex interactions observed in nature. Studies in this field draw parallels from a variety of species, ranging from amoebae [5] and insects like ants [6] and bees [7], to larger organisms such as birds and fish [8]. These biological systems, characterized by simple yet scalable interactions, have significantly influenced robotics research [9], [10].

A common approach in swarm robotics research is using computer simulations [8]. While simulations offer cost-effective and rapid means to test algorithms, they often fall short in replicating real-world conditions. Physical robots, therefore, play a crucial role in bridging this gap, allowing for the validation of simulated models in real-world applications.

The design of swarm robots presents unique challenges, particularly in the development of a perception system that facilitates swarm interaction. Traditional methods often rely on external motion capture systems, such as Vicon [11], Optitrack [12], Loco Position [13], and Lighthouse [14]. While these systems help to perception of swarm robots, limit the robots to structured environments and struggle to scale in large swarm experiments. Consequently, there has been a shift towards swarm robots capable of operating autonomously using onboard resources.

Swarm robots are generally categorized based on their sensing systems. The first category includes infrared-based (IR) range and bearing systems [15], prevalent in many mobile robots and adapted for aerial robots despite weight challenges [4], [15]. The second category encompasses vision-based systems that utilize cameras and im-
age processing techniques [16], [17], [18]. Advances in microprocessors have made these systems more viable, although they still face issues in accurately predicting the position of neighboring robots. The third category involves relative localization systems based on ultrawide-band communication [13], [19], [20], [21], [22], which are particularly suited for flying robots due to their omnidirectional sensing capabilities. However, these systems face challenges in obstacle detection and depend heavily on communication.

This thesis aims to develop two modular range and bearing systems that enable swarm robots to function effectively in cluttered environments. We utilized time-of-flight (ToF) sensors capable of measuring distances and distinguishing between obstacles and neighboring robots. Two systems were developed, employing sensors with similar technology but tailored for specific applications. These systems are designed to integrate seamlessly into diverse robotic platforms, supported by common communication protocols like I2C and SPI.
Swarm robots have evolved around relative localization and communication systems for years. When we examine the literature, we come across many systems that perform these tasks together. It would be wrong to separate the "range and bearing systems" that swarm robots use to separate neighboring robots and obstacles from each other from the swarm robot literature. For this reason, this literature review starts with swarm robots shaped around range and bearing (RnB) systems. It continues with relative localization systems in swarm aerial robots, which is a challenging area. Finally, the time of flight (ToF) based range and bearing system presented in this thesis are compared with other studies in the literature.

2.1 Swarm Robots with Infrared Range and Bearing (IR-RnB) System

Infrared-based range and bearing systems (IR-RnB) have an important place in swarm robotics. These systems generally work on the principle that a robot emits infrared light, which is reflected from another object or robot and then detected back by sensors. The intensity of this reflected light indicates the distance as range, while the sensor that detects this light provides the bearing angle due to the geometry of the system. In addition, in many robots or systems, a special pattern or code is embedded in the emitted IR light. When the reflected light contains this pattern, it signals interaction with a robot, so that the robot can distinguish between neighboring robots and obstacles. Swarm-bot[1] uses IR sensors for both navigation and communication. Similarly, Alice[23] and E-puck[3] use circular infrared arrays. These arrays measure distance by changes in IR signal intensity, while the position of the sensor
provides directional information. Kilobot\textsuperscript{2} senses its surroundings using modulated IR light. The dual-purpose system estimates proximity and enables inter-robot messaging, making it ideal for large-scale swarm studies.

Mona\textsuperscript{24}, Khepera 4\textsuperscript{25} and GRITSBot\textsuperscript{26} use infrared-based range and bearing systems for localization. These robots need different hardware for communication. Droplet\textsuperscript{27} uses a unique combination of RGB LEDs and photodiodes, providing distance and direction information based on light intensity. This rather small robot is used for many swarm algorithms. Finally, Eyebot\textsuperscript{4} was developed as part of the European Union-funded “Swarmonoid” project\textsuperscript{28}. It is the only infrared-based range and bearing system that can also be used by drones. The infrared transmitters and receivers are placed in three dimensions and weigh about 250 grams. This relative localization system requires a huge indoor drone to carry it. Although the system is useful, it is not suitable for micro-air vehicles used in indoor environments. In summary, these robots exemplify the integral role of infrared systems in swarm robotics, emphasizing the field’s quest for simplicity, compatibility, and efficiency.

2.2 Other Relative Localization Technologies Suitable for Swarm Robots

A major factor in the use of infrared-based systems in swarm robotics is the minimalist construction of the robots. Robots continue to use infrared sensors with low power requirements, low processing power, and small dimensions. However, nowadays, thanks to low-power microcontrollers that can even process images, some relative localization systems based on vision, ultrawide-band, and audio processing have
emerged.

Initially, vision-based systems were based on estimating the position of robots and obstacles using data from onboard cameras\cite{16}, \cite{17}, \cite{18}. Nowadays, although there are systems that detect obstacles using a combination of optical flows and inertial measurement units, it is still a challenge for robots to find the position of neighboring robots in real time. There have been studies that calculate the position of neighboring robots by placing markers on them. However, it should be noted that these systems require a structural environment. In addition to these, there are studies aiming to find neighboring robots with deep learning. The limited payload and onboard processing capacity of indoor drones make it difficult to apply these methods to them.

Secondly, Ultra Wide Band (UWB) \cite{13}, \cite{19}, which is used for short-distance communication, is very successful in distance sensing with its signal strength. Robots can calculate their own position thanks to the signals coming from these anchors placed in the environment. This system used for global positioning was developed for robot swarms. All robots share their own statuses thanks to this system. Thanks to UWB, robots measuring range estimate each other’s positions. Although this omnidirectional system is suitable for drones’ actuation systems, it cannot detect obstacles around them. In addition, the system requires high bandwidth communication\cite{20}, \cite{21}, \cite{22}. It is not scalable for swarm robots.
2.3 Contribution of Time of Flight Based Range and Bearing System

In the present work, we address a fundamental challenge in the domain of swarm robotics: onboard sensing. While traditional approaches have primarily focused on infrared (IR) range and bearing systems, recent technological advancements have shifted this landscape. Our contributions lie in the integration of Time-of-Flight (ToF) sensors—specifically, the VL53L1 and VL53L5 which are both compact and efficient. Although these sensors have previously been employed for obstacle detection, we introduce novel algorithms for robot detection. These algorithms require significantly lower computational power and communication overhead compared to vision-based and Ultra-Wideband (UWB) systems, representing a considerable advancement for swarm robotics. Our multi-target tracking module, based on a novel robot detection method, allows for the effective estimation of robot states with minimal data requirements. This makes it an ideal framework for range and bearing systems across various swarm settings. Importantly, our system is not just tailored for mobile robots; its sensing capacity of 1.3 and 1.7 meters and lightweight design make it suitable for micro-aerial vehicles as well. To foster collaborative research, we have adopted an open-source approach, providing both the design and code, and have employed widely-used I2C and SPI communication protocols to make the system accessible for researchers in the swarm robotics community.

To sum up, ToF range and bearing systems:

- Incorporate compact, state-of-the-art Time-of-Flight (ToF) sensors to significantly improve onboard sensing capabilities.
- Introduce pioneering robot detection algorithms that operate with reduced computational and communication resources.
- Feature a multi-target tracking module that provides efficient state estimation of robots, even with minimal available data.
- Demonstrate versatility by being adaptable to both land-based and micro-aerial swarm robotic platforms.
- Utilize open-source design and code, as well as standard I2C and SPI commu-
communication protocols, ensuring accessibility and facilitating continued innovation in the swarm robotics research community.
CHAPTER 3

RANGE AND BEARING SYSTEM HARDWARE DESIGN

The design of the range and bearing system using time-of-flight (ToF) sensors necessitates a harmonious integration of various components, each playing a critical role in the system’s functionality. A key aspect of this design is ensuring that the system follows strict size and weight constraints, making it suitable for use with micro aerial vehicles (MAVs) and tiny mobile robots.

Several factors must be considered to achieve this harmony. They include ensuring a regulated voltage supply to the sensors, effective communication between the sensor and microcontroller, and between the microcontroller and the robot. Additionally, the communication between the microcontroller and the USB port is equally important for data transmission and system management.

The hardware architecture of the range and bearing systems is composed of two main printed circuit boards (PCBs). The first is the daughterboard, which has all the sensors and the necessary components for their operation. This board is the heart of the sensing mechanism, containing the vital electronics that gather the environmental data.

The second PCB is the motherboard. This board acts as a platform where the daughterboards are connected. It ensures that all sensors function coherently, coordinating their activities to produce an output. This integration is essential for the smooth operation of the range and bearing system.

A noteworthy point in the design is the different fields of view offered by the VL53L1 and VL53L5 sensors. These variances and the overall geometry of the range and bearing system significantly influence the interest area of the system. The design
Figure 3.1: Top and front view of two RnB systems with the relative position variables \( \{d, h, \theta, \psi\} \), FoV of sensor symbolized with \( \phi \) and angle between consecutive sensors symbolized with \( \beta \)

must account for these differences to optimize the system’s sensing capabilities, ensuring accurate and efficient detection and tracking within the intended operational environment.

3.1 VL53L1 Time of Flight Based Range and Bearing System

3.1.1 Geometry of the VL53L1-Based System

The VL53L1-based system is characterized by its unique geometric configuration. Twelve VL53L1 time of flight (ToF) sensors are arrayed in a circular pattern on the motherboard, each providing a 27-degree field of view and spaced at 30-degree intervals. This arrangement offers a nearly continuous monitoring perimeter around the device, effectively balancing coverage and sensor density.

The system’s design addresses the challenge of blind spots, which are inevitable due to the limited number of sensors. At the maximum range of 1.3 meters, the blind
zones expand to about 90mm from Eqn [3.1]. This is mitigated by ensuring that objects larger than 10 cm in diameter remain detectable, an important consideration for the intended use with MAVs and tiny mobile robots.

\[ w = 2d \left[ \tan \left( \frac{\beta}{2} \right) - \tan \left( \frac{\phi}{2} \right) \right] + g_s \] (3.1)

The system accommodates slight altitude variations for MAVs operating in three-dimensional spaces within a range of ±156mm from Eqn [3.2]. This geometric adaptation is essential for maintaining operational effectiveness in typical 2D scenarios while allowing minor vertical movements in MAV formations.

\[ \Delta h = \pm d \cdot \tan \left( \frac{\phi}{2} \right) \] (3.2)

### 3.1.2 Electronic Components, Specifications, and Power Management

The microcontroller of the system is the STM32F103 MCU, which interfaces with the twelve ToF daughterboards. Each daughterboard houses a VL53L1 sensor optimized for short-distance measurement mode in swarm robot applications, limiting the detection range to 1.3 meters.

The design emphasizes compactness and lightness, measuring only 50mm wide and weighing 12.5 grams. This design ensures the system’s suitability as a payload for MAVs and compatibility with tiny robots. Power efficiency is also a key feature, with the system requiring a modest 3.3V and 170mA, aligning with the energy constraints of tiny mobile robot platforms.

Cost considerations are integral to the system’s design. The total cost of the system is around 90 US dollars, making it a budget-friendly option in the range and bearing market.

In alignment with our open-source commitment, the motherboard and the daughterboard are designed using open-source software, facilitating community-driven improvements and adaptations.
3.1.3 Communication Systems and Protocols

The communication architecture of the VL53L1-based system is a critical component of its functionality. The system primarily relies on i2c connections for effective data transfer and control. This setup involves a dual i2c link: one connecting the VL53L1 sensors on the daughterboards to the central STM32F103 MCU on the motherboard and another linking the motherboard to the robot.

The i2c protocol is particularly suited for applications requiring multiple sensors to interact with a microcontroller, as it simplifies wiring and data synchronization.

In our design, the motherboard’s role as a communication hub enables sensor data integration, providing a feed that the robot’s control systems can use to make informed decisions. This integration is crucial for swarm robotics applications where real-time data and rapid response are paramount.

Moreover, using i2c communication ensures a streamlined and cost-effective design, avoiding the need for more complex and expensive communication systems. This choice reflects our commitment to creating a balance between functionality, affordability, and ease of replication, in line with our open-source ethos.

3.1.4 Integration with Robots

Integrating the VL53L1 range and bearing system with both MAVs and mobile robots, involves challenges specific to each type of robot.

3.1.4.1 Integration with MAVs

For MAVs, the primary concern is ensuring that the additions do not adversely affect flight dynamics. A key solution to this challenge involves the strategic mounting of the system. The RnB system is attached to the upper section of indoor drones with an elevation mechanism. This mechanism is crucial in preventing the sensors from mistakenly detecting the drone’s own propellers. To facilitate this, we recommend using snap-fit 3D printed components, which provide flexibility and ease of assembly.
Our open-source designs for these components are available. (Link)

### 3.1.4.2 Integration with Mobile Robots

For mobile robots, the placement of the system is critical to mount the system at a height that ensures it does not detect the ground. This positioning is essential for the system to function correctly, as it relies on accurately identifying and tracking objects within its environment.

### 3.2 VL53L5 Time of Flight Based Range and Bearing System

#### 3.2.1 Geometry and Field of View of the VL53L5-Based System

The VL53L5-based system is designed with a strategic geometric configuration that significantly enhances its applicability for micro aerial vehicle swarms. Central to this design is the circular arrangement of eight VL53L5 ToF sensors on the motherboard. The field of view of each sensor is approximately 45 degrees, a substantial increase from the previous 27 degrees offered by the VL53L1 ToF sensor. This expanded field of view is pivotal in eliminating blind zones, ensuring an almost uninterrupted coverage area.

This design aspect is particularly advantageous for MAVs operating in three-dimensional environments. The wider field of view allows for a more comprehensive monitoring capability, ensuring consistent detection even with variations in altitude among MAVs. The VL53L5-based system can accommodate height differences more effectively, computed as $\pm 700\text{mm}$ with Eqn 3.2 which translates to enhanced flexibility and synchronization in MAV swarms.

The arrangement and capabilities of these sensors not only facilitate a fuller coverage but also make the system significantly more immune to the challenges posed by varying heights in MAV formations. This makes the VL53L5-based system an ideal choice for MAV applications, where maintaining consistent detection and coordination across different altitudes is crucial.
3.2.2 Electronic Components and Specifications

The RP2040 microcontroller on the motherboard is central to the system, interfacing with the VL53L5 ToF sensors on individual daughterboards. The sensors are notable for their accuracy and dual-mode functionality, offering a 4x4 multizone mode at 60Hz for rapid data processing and an 8x8 multizone mode at 15Hz for low-resolution imaging. The entire assembly, measuring 55mm in width and weighing just 10 grams, is cost-effective, costing 80 US dollars, making it an economically viable solution.

3.2.3 Power Requirements and Communication Protocols

The VL53L5-based range and bearing system is made to use power efficiently and communicate effectively. It uses an I2C communication protocol with 1 MHz bandwidth for connecting eight sensors on two different I2C lines. There’s also a Modbus communication option to make it more flexible in sending data to robots.

Modbus, known for its reliability and widespread adoption in industrial environments, offers a robust method for data exchange. Its integration into our system allows for seamless and versatile communication, especially beneficial in complex swarm robotics applications requiring different types of data transmission methods. The Modbus protocol offers an alternative pathway to provide durable communication.
like the SPI communication.

The motherboard’s design, featuring a 4-layer PCB, and the daughterboards with a 2-layer PCB layout, are optimized to support these communication protocols efficiently. This multi-protocol communication capability ensures that the system remains adaptable to diverse robotic platforms, enhancing its applicability in MAVs and mobile robots.
CHAPTER 4

RANGE AND BEARING SOFTWARE SYSTEM

The integration of range and bearing systems into robot swarms marks a significant step in the field of swarm robotics. This process, crucial for the efficient functioning of the swarms, necessitates comprehensive software modifications. These modifications are driven by two primary challenges encountered in the swarm environment.

Firstly, the operation of swarm robots inherently introduces a considerable amount of noise into their environment. This noise affects the accuracy of sensor readings, posing a challenge to the reliability of the data these sensors provide. Accurate sensor measurements are essential for the precise navigation and coordination of the robots within the swarm.

Secondly, a function of the software is to enable the robots to distinguish between their kin robots and obstacles in the environment. This capability is vital for effective swarm operations. Interestingly, the noise generated by the swarm robots themselves aids in this process. The characteristics of the noise can be used by the software to help differentiate between robots and obstacles.

In the following section, we explore the specific software enhancements that have been developed to address these challenges. These enhancements are tailored to two types of range and bearing systems. While the software for both systems shares a common goal of enabling robot detection, they differ in their approach. This difference is primarily due to the VL53L5 ToF sensor’s ability to perform multi-zone object detection, which allows for the inclusion of image processing-based algorithms in the software.

Through these software enhancements, the range and bearing systems become better
in the dynamic and challenging environment of robot swarms.

4.1 VL53L1 Based Range and Bearing System

4.1.1 Robot Detection Algorithm

The Time-of-Flight Range and Bearing (ToF RnB) system, designed for detecting robots, is groundbreaking in its nature. The identification of robots is intricately linked with the ranging sequence of the sensor. Hence, initially, we outline the sensor’s ranging sequence.

A ranging sequence of the sensor comprises three distinct measurements, as depicted in Figure 4.1, which are invariably consecutive and cannot be treated independently due to the constraints imposed by the VL53L1 API. The first measurement by the sensor is referred to as ambient, during which the receiver end of the sensor captures infrared (IR) signals at a wavelength of 940[nm] that exist in the surroundings. The sensor’s emitter remains inactive during this phase. The second measurement sequence, labeled as signal, involves the sensor emitter transmitting a 940[nm] signal with a specific pattern, subsequently collected by the sensor’s receiver as a reflected signal. The ambient reading obtained during the first sequence is employed to correct the signals from signal, enabling the calculation of the signal-to-noise ra-
This ratio determines the validity of the measured range. Moreover, using emitting sequences employing diverse signal patterns addresses the challenge of sampling encountered in radar systems. This challenge arises when echoes beyond the system’s maximum unambiguous range are received as if they were within the valid range.

Incorporating an external random delay after a ranging sequence is the final step. This random delay spans a fixed period, denoted as $t_d$, and ideally holds a $1/2$ probability of occurring, as it hinges on a randomly seeded binary variable. For brevity, ambient signifies the signal reading when the emitter is inactive, while signal denotes the signal reading when the emitter is active. These readings share the same unit of measurement: kilo-count per second [kcps].

Analogous to Kobot-I’s IR RnB system[15] is explained in Chapter 2, and many other communication networks that employ a common carrier, the ambient reading of the ToF sensor functions as a ‘carrier sense.’ For the ToF sensors, the carrier constitutes 940[nm] IR light, and ’sense’ denotes ambient measurement without signal emission. Assuming that ‘carrier access’ is solely granted to the emitters of other robots—true indoors and outdoors without sunlight—one can infer that signal collision sensed in the carrier corresponds to another robot within the sensor’s FoV.

Figure 4.1b illustrates the externally introduced random delay’s role and contribution to ensuring robot detection. The sequences elucidated in Figure 4.1a are presented continuously, and the random delay is incorporated into the ranging cycles of robot 1 and robot 2. Initially, the worst-case scenario is considered, where both sensors operate in synchrony. As depicted, the white regions, corresponding to ambient reading, occur concurrently, indicating that neither robot 1 nor robot 2 detects the signal emitted by the other robot. Consequently, no robot detection is reported. However, in the subsequent ranging cycle, owing to the random delay of robot 2, the signal sequence of robot 1 coincides with the ambient reading of robot 2. As a result, robot 2 registers a non-zero ambient reading and reports it as the presence of robot 1 (indicated as r 1,2 4). Conversely, robot 2 refrains from reporting robot detection since, during its ambient reading phase, robot 2 was subjected to a random delay and emitted no signal. In the third ranging cycle, ambient reading phases for both robot 1 and robot...
2 align with the \textit{signal} phases of the other robot, prompting a robot detection report.

The primary purpose of random delay is to enable robots within a swarm to detect each other without needing precise timing or scheduling. In a hypothetical scenario where two robots are perfectly synchronized, they wouldn’t detect each other without the random delay. However, the random delay introduces a 50% chance that in the next cycle, the robots are out of sync and detect each other. This probability comes from one of the robots experiencing a delay. For the other 50% probability, both robots either delay or not, restoring synchronization. Therefore, robot detection becomes practically certain with high-frequency sampling and a substantial data buffer.

Notably, a higher sampling frequency reduces the accuracy and consistency of range readings. Yet, even at the highest sampling rate of 66[Hz], the precision remains suitable for swarm algorithms. Considering this and the sensor’s 66[Hz] limit, a buffer holding the five most recent readings was developed. Since our robots move relatively slowly ($< 0.5[m/s]$) and can’t exit the sensor’s field of view within $\frac{66}{5} = 13.2[Hz] \to 76ms$, even if one of the last five readings indicates a robot’s presence, the subsequent reading is treated as a robot detection.

\section*{4.1.2 Data Filtering and Error Correction Approach}

In the dynamic world of swarm robotics, where precision meets the challenge of collecting data at high speeds, a refined method for filtering data and correcting errors becomes essential.

Central to this method is carefully managing data buffers within the sensor system, each serving specific roles: 'ambient,' 'signal,' 'range,' and 'robot detection.' These buffers act as temporary storage, allowing real-time analysis and filtering to remove unreliable values.

The filtering process follows a clear sequence:

1. **Filtering Out-of-Range Values:** This step identifies and fixes outlier range values beyond the sensor’s maximum limit by substituting them with the maximum value. This helps prevent skewed data from distant objects.
2. **Checking Median Signal**: By comparing the median value from the signal buffer to a set threshold, the process ensures the accuracy of range values, guarding against compromised readings.

3. **Handling Data Variability**: Utilizing insights from the interquartile range (IQR), this step examines the distribution of range buffer data. Elevated IQR values indicate potential anomalies and trigger the removal of questionable data points.

### Algorithm 1: Robot detection, random delay and filtering

```
range=maxRange; // Initially no object detected
isRobot=false; // Initially no robot detected
iqrAmbient, medianAmbient = IQR(circularBuffAmbient);
iqrRange, medianRange = IQR(circularBuffRange);
if iqrAmbient > ambientThresh then
    circularBuffIsRobot.update(true); // Update with robot detection
else
    circularBuffIsRobot.update(false); // Update with no robot detection
if circularBuffIsRobot.any() then
    isRobot = true; // At least one robot detection in buffer
if (iqrRange < rangeThresh) and (signal > signalThresh) then
    range = medianRange; // Valid object range
if randomBool() and !isWait then
    isWait = true; // Will delay in next cycle
```

Signal interference and noise inherent in swarm robotics require smart solutions. The application of a specialized reflective coating enhances signal quality. Relying on the median value from the range buffer ensures accurate distance calculation, prioritizing precision over raw sensor output.
Addressing environmental biases involves an ‘ambient’ buffer, usually with five data points. This buffer detects and quantifies ambient biases. A higher interquartile range (IQR) indicates object presence, often robots.

A ‘robot detection’ buffer is used for reliable robot detection, typically containing five data points. Even one robot reading identifies an entity as a robot, while a continuous sequence of five non-robot readings signifies an obstacle. This minimizes incorrect classifications.

This comprehensive data filtering and error correction approach strengthens the swarm robotics framework against inaccuracies. By carefully filtering data, adjusting for environmental biases, and intelligently interpreting sensor signals, the system is ready for informed decision-making and smooth coordination.

### 4.1.3 Multi-Target Tracker (MTT)

Multi-Target Tracker (MTT) probabilistic tracks neighboring robots using range and bearing readings. It estimates the positions and velocities of actively tracked robots. We can say that MTT has three main tasks. It can manage tracks with these tasks.

- **Initiate** a new track with incoming measurements.
- **Incoming readings** Associate existing tracks, **Update** the tracks to which the readings belong, and **Estimate** the current state of the tracks.
- **Delete** tracks that have not been updated for a while.

In our study, we focus on a team of \( N \) robots, each equipped with a Time-of-Flight (ToF) range and bearing system. It is important to note that there is no communication between robots in this setup. At each time instance \( k \), a robot acquires a set of measurements from its onboard sensor, thereby allowing us to track the relative positions and velocities of neighboring robots. Specifically, each robot \( i \) is represented in a relative coordinate frame.

\[
x_i = [x_{i,\text{pos}}, x_{i,\text{vel}}, y_{i,\text{pos}}, y_{i,\text{vel}}]^T
\]
In this expression, $x_{i,\text{pos}}$ and $x_{i,\text{pos}}$ correspond to the relative position coordinates, and $x_{i,\text{vel}}$ and $y_{i,\text{vel}}$ represent the relative velocity components.

In our case, we capture the relative states of neighboring robots by utilizing a constant velocity motion model. This model is pivotal for making accurate predictions about the positions and states of future time steps.

The mathematical formulation for the motion model is given by Equation 4.1:

$$x_{k+1}^i = f(x_k^i, q) = A_k x_k^i + Q_k$$  \hspace{1cm} (4.1)

Here, the state transition matrix, denoted as $A_k$, and the process noise covariance matrix, denoted as $Q_k$, are defined as:

$$A_k = \begin{bmatrix} 1 & \delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \delta t \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad Q_k = \begin{bmatrix} \frac{\delta t^2}{2} & 0 & 0 & 0 \\ 0 & \delta t & 0 & 0 \\ 0 & 0 & \frac{\delta t^2}{2} & 0 \\ 0 & 0 & 0 & \delta t \end{bmatrix}$$  \hspace{1cm} (4.2)

In these equations, $\delta t$ represents the time interval between consecutive samples at a particular time $T$. The acceleration of the robots, denoted as $q$, is assumed to follow a Gaussian distribution, $q \sim \mathcal{N}(0, \mathbf{Q})$.

We further incorporate a sensor model to account for the readings from our range and bearing system. The sensor model is described by Equation 4.3:

$$h(x, x_e) = \begin{bmatrix} \theta \\ r \end{bmatrix} = \begin{bmatrix} \arctan \left( \frac{y - y_e}{x - x_e} \right) \\ \sqrt{(x - x_e)^2 + (y - y_e)^2} \end{bmatrix} + \eta$$  \hspace{1cm} (4.3)

In this context, $\eta$ represents the measurement noise and is modeled as Gaussian white noise, $\eta \sim \mathcal{N}(0, \mathbf{R})$. The variable $x_e$ indicates the position of the ego robot, which is the reference robot from whose perspective the relative motion and sensor data are being considered.

To track the states of the robots, we first need to find out which track the incoming
readings are related to. One could say that this is a nice association problem.

Addressing the association problem in range and bearing involves carefully choosing from a plethora of existing algorithms, including but not limited to Global Nearest Neighbour (GNN), Joint Probabilistic Data Association Filter (JPDA), Probability Hypothesis Density (PHD) filters, and Density filters. Each algorithm has unique advantages and limitations, which are pivotal when considering various factors specific to our use case.

- **GNN**: This algorithm employs a linear cost assignment problem as its underlying mechanism. It associates measurements to tracks by calculating a cost via a specific distance metric and then minimizes this cost to identify the most likely measurement-track pairings.

- **JPDA**: Unlike GNN, JPDA evaluates all feasible measurement-track combinations, assigning probabilities. The main drawback of JPDA is its elevated computational cost, especially as the number of agents increases.

- **PHD and Density Filters**: These filters use a Random Finite Set (RFS) approach to represent both tracks and measurements, enabling them to update estimates without explicit measurement-to-track associations.

To decide which of these methods to use, we need to analyze our problem well. To list the criteria that affect our choice:

- **Sensor Characteristic**: Our sensor suite is optimized for a very low rate of false positive readings, meaning that clutter is minimal. However, it is prone to false negatives and often misclassifies robots as obstacles.

- **Maximum Number of Track**: The sensor suite can detect around 3-4 neighboring robots in a crowded swarm environment.

- **Computational Complexity**: Given our swarm robots’ limited computational resources and power, the selected algorithm must be lightweight.

- **Accuracy and Robustness**: While accuracy is important, it may be compromised to some extent to maintain low computational overhead.
Considering the above factors, we have chosen the Global Nearest Neighbour algorithm for our application. GNN offers a good balance between computational efficiency and reasonable accuracy, particularly in environments with minimal clutter. During each time step $k$, the GNN algorithm receives incoming measurements and updates three essential lists: the Active Track List $L_a^k$, the Holding Track List $L_h^k$, and the Unassociated Measurement List $L_u^k$. A detailed pseudocode representation of the GNN algorithm is provided in Algorithm 2.

This selection is especially pertinent given our specific constraints and requirements, and GNN’s relative ease of implementation and performance characteristics make it well-suited for our application.

In our model, each active track, labeled as $T_i^k$, is characterized by a set of prediction mean and covariance, expressed as $(\mu_i^k, P_i^k)$. These are evaluated at a specific time index $k$. The conventional Kalman Filter prediction technique is employed to refine these estimates iteratively, guided by the motion model detailed in Equation (4.1).

### 4.1.3.1 Association and Update:

Before estimating these tracks, it’s essential to link new measurements with existing tracks. Any measurements that can’t be linked, are stored in a separate list, $L$, for possible future track formation.

To organize this, we calculate a cost matrix $D$, designed to assess the best matches between tracks and new measurements. For each potential match, the Mahalanobis distance measures the statistical difference between the prediction $(\mu_i^k, P_i^k)$ and the new measurement $z_j^k$:

$$D_{ij} = \sqrt{(z_j^k - h(\mu_i^k))^T P_k^{-1} (z_j^k - h(\mu_i^k))}$$  (4.4)

Each value of $D_{ij}$ is compared to a predefined threshold $d_{out}$ to identify and remove outliers.

Once this matrix is complete, we apply the Hungarian algorithm to determine the
optimal associations between tracks and measurements. After that, a standard Kalman Update process revises the track estimates. It’s worth noting that any tracks without a new associated measurement are not updated.

**4.1.3.2 Track Initiation and Deletion:**

In swarm scenarios, the number of detectable robots can fluctuate. To handle this, our Multi-Target Tracking (MTT) module must be able to create new tracks and eliminate outdated ones.

For track deletion, we compare the trace of each track’s covariance matrix $P_i^k$ to a deletion threshold $d_d$. If the trace exceeds this value, the track is removed.
For track initiation, we follow a more nuanced approach. While generating new tracks for all unlinked measurements in $L^u_k$ may seem straightforward, this can lead to false or noisy tracks. To address this, a ‘holding track’ is created for each unlinked measurement and stored in a separate list $L^h_k$. Over time, attempts are made to link these holding tracks with new measurements in $L$.

If a holding track gathers $n_d$ measurements and its covariance trace is below $d_d$, it’s upgraded to an active track. It is discarded if a holding track remains unlinked for a set period.
Algorithm 2: MTT using GNN Algorithm

**Input**: Time step $k$, $Z_k$, $L_{k-1}^a$, $L_{k-1}^h$, $L_{k-1}^u$

**Output**: $L_k^a$, $L_k^h$, $L_k^u$

**foreach** Track $T^i$ in $L_{k-1}^a \cup L_{k-1}^h$ **do**

$T^i \leftarrow$ Prediction($T^i$); 

**end**

Calculate Matrix $D$ in (4.4);

Find optimal measurement-to-track assignments using $D$;

**foreach** Successfully Associated pair ($T^i$, $z^j$) **do**

$T^i \leftarrow$ Update($T^i$, $z^j$);

**end**

Insert unassociated measurements to $L^u$;

**foreach** Track $T^i$ **do**

if Trace of Covariance $\geq d_d$ then

Delete Track $T^i$;

end

**end**

**foreach** Holding Track in $L^h$ **do**

if Number of Associated Measurements $\geq n_a$ then

Add Track to $L^a$;

end

if No Associated Measurements for 1 Second then

Delete Track;

end

**end**

4.2 VL53L5 Based Range and Bearing System

In this section, we delve into the intricacies of the VL53L5 time-of-flight (ToF) sensor, a sophisticated component integral to our range and bearing system. This sensor, while operating on principles similar to its predecessor, the VL53L1, as discussed earlier, introduces advanced functionalities that enhance its application in swarm
robotics.

The operation of the VL53L5 ToF sensor can be understood through three distinct phases:

1. **Ambient Phase:** Initially, the sensor engages in an observation mode, where it listens to the environment without emitting any light. This phase is critical for measuring the ambient conditions, setting the stage for accurate data acquisition.

2. **Signal Phase:** Following the ambient phase, the sensor emits light in specific patterns. It then collects the returning light rays, a process crucial for calculating the distance and identifying objects in its field.

3. **Processing Phase:** In the final phase, the sensor processes the incoming signals. During this phase, no active measurement occurs. The necessity for this processing phase arises from the sensor’s high-capacity functionality. Notably, the VL53L5 can detect an area almost twice as large as its predecessor.

One of the standout features of the VL53L5 sensor is its ability to divide the area of interest into a grid of 64 zones. This segmentation allows for detailed data acquisition from each part of the grid. The sensor captures a variety of data points, including range, ambient, SNR (signal noise ratio), reflectivity ratio, and other pertinent information for each segmented area.

The multi-zone measurement capability of the VL53L5 essentially endows it with the attributes of a low-resolution depth camera. This unique feature has led us to incorporate image-processing techniques in our software system. These techniques enable the sensor to interpret and analyze the data with enhanced accuracy and depth, significantly contributing to the sophistication of the swarm robotics system.

### 4.2.1 Object Detection

The VL53L5 ToF sensor, which we have described as similar to a low-resolution depth camera, plays a key role in our object detection strategy. The main goal of
this sensor is to identify and categorize objects within its measurement. We need to determine whether these objects are kin robots or obstacles. Before classifying objects, we need to segment objects from each other. To achieve this, we set two rules that decide whether reading comes from the same object or different objects.

1. **Depth-Based Segmentation:** The first approach is based on depth measurements. We presume that segments of the same object have similar depth readings. To identify these segments, we utilize histogram analysis. This method groups measurements with similar depth, allowing us to outline distinct objects. The specifics of the histogram analysis method are elaborated in the following chapter.

2. **Spatial Segmentation:** The second approach focuses on the spatial arrangement of measurements. We operate assuming that measurements from the same object are located close to each other. To effectively link these measurements, we apply the connected component labeling method. This method helps us understand the spatial continuity of the measurements, offering a clearer picture of each object’s shape and size.

These methods, histogram analysis, and connected component labeling form the core of our object segmentation strategy. Each is designed to exploit a specific aspect of the sensor’s data—depth or spatial arrangement. This dual-method approach enables us to process the sensor data accurately and efficiently, paving the way for precise object identification and categorization in our swarm robotics system. Detailed explanations of these methods are provided in the subsequent chapter.

### 4.2.1.1 Histogram Analysis

The utilization of histograms plays a pivotal role in the segmentation of objects as detected by the sensor. This technique hinges on analyzing the distribution of object distances within the sensor’s field of view.

The process begins by generating a histogram from the sensor’s measurements. This histogram effectively maps out the spread of distances of various objects in the sen-
By examining this distribution, we can group measurements that are closely spaced, and likely belong to the same object.

To refine this approach, we set a specific step value for the histogram. This step value helps in identifying the start and end points of what we term our 'interest distance'. The beginning of this range is marked by the first non-zero reading that remains consistent over the step intervals. Conversely, the end of the range is denoted by the last non-zero distance reading. Measurements that fall within these bounds are considered potential parts of the same object.

This method enables us to delineate areas within the histogram that may contain multiple objects. These areas, once extracted, can be visualized as binary images. We refer to these binary visualizations as object masks. These masks provide a clear and simplified representation of the areas where objects are likely located.
By employing this histogram-based approach, we gain a nuanced understanding of how objects are distributed within the sensor’s field of view. This understanding is crucial for accurate object segmentation and plays a fundamental role in the overall functionality of our swarm robotics system.

### 4.2.1.2 Connected Component Labeling

Following the creation of binary images as object masks through histogram analysis, we employ connected component labeling (CCL) to further refine our object identification process. This method is essential in distinguishing and labeling different objects within the binary image.

Connected component labeling is a technique used to detect connected regions in binary images. In our project, we specifically utilize CCL with 4-connectivity. This means that for any given pixel, we consider its four adjacent pixels (up, down, left, right) as potentially belonging to the same object. Diagonal neighbors are not considered in 4-connectivity, which helps prevent the accidental merging of separate but diagonally close objects.

The process involves scanning the binary image, pixel by pixel, and assigning labels to different components (objects) based on their connectivity. When a pixel belonging to an object is encountered, it is labeled with a unique identifier. As the scan progresses, adjacent pixels that are part of the same object are assigned the same label, while non-adjacent pixels are labeled differently.

![Binary image before connected component labeling](a) (b) (c) Binary images created from CCL

Figure 4.8: a) Binary image before connected component labeling, b,c) Binary images created from CCL
Through connected component labeling with 4-connectivity, we can accurately distinguish between individual objects that may reside within the same interest distance range. This distinction is crucial when multiple objects are close together, as it enables us to treat them as separate entities in our analysis.

The outcome of this process is a more detailed and segmented representation of the scene, with each distinct object clearly identified and labeled. This refined segmentation is essential for the subsequent steps in our object detection and classification system, forming a critical component of our overall approach in swarm robotics.

4.2.2 Classification of Objects: Robot Detection

In the advancement of our swarm robotics system, a crucial step following the identification of objects is determining whether these objects are robots or obstacles. This classification is essential for the effective operation of the swarm and hinges primarily on the detection of broadcasts from the identified objects.

Recalling the sensor’s measurement processes discussed earlier, particularly the ambient phase, our sensor is designed to be receptive to signals from the environment. It is during this phase that the sensor’s ability to detect signals becomes key in identifying robots. Specifically, the presence of signals in the area where an object is located is indicative of a robot. These signals, emanating from the robots, are distinguishable from the ambient noise and other environmental factors.

![Figure 4.9: The ambient channel readings of the sensor.](image-url)
Figure 4.10: Figures demonstrate robot detection algorithm of VL53L5 based RnB system. Figures (a,b,c) show that binary images are created with histogram analysis and connected component labeling. Figure (d) shows the ambient channel of the sensor for robot detection. Figure (e) shows the final image is sent to the robot after processing is done.

Therefore, we infer the nature of the detected object based on the intensity of ambient measurements. If the ambient measurements in a specific area exceed a predetermined threshold value, it suggests that the object in question is likely a robot. This threshold is set based on the typical signal strength emitted by the robots, distinguishing them from obstacles.

This classification method leverages the sensor’s sophisticated measurement capabilities, enabling it to discern between kin robots and obstacles effectively. By identifying the nature of each object, the system can make informed decisions in the coordination and navigation of the swarm, ensuring optimal functionality and efficiency.

In the final stage of our process, the identified positions of neighboring robots and obstacles are communicated to the robot. This crucial step ensures that each robot in the swarm has the necessary information to make informed decisions about its movements and interactions. We employ communication protocols or interfaces such
as Modbus or SPI to facilitate this data transfer. These methods are chosen for their reliability and efficiency in handling the data exchange within the robotic system. Each robot receives accurate and timely updates about its surroundings through the Modbus protocol or SPI (Serial Peripheral Interface), enabling the swarm to function cohesively and respond dynamically to the ever-changing environment.
All experiments were conducted using Kobot CoRe swarm robots equipped with our RnB systems. This section initially explains the Kobot Core robotic platform. The RnB system was implemented in various Kobot configurations: simulated, wheeled, and flying. Furthermore, we designed an experimental framework to evaluate the effectiveness of the RnB system, utilizing the Kobot infrastructure for all test scenarios.

5.1 Kobot Core Platform

The experimental framework for this thesis involved utilizing Kobot robots, which operate under a modular and interchangeable architecture known as the CoRe (Common Architecture). The CoRe systems provide an effective methodology for segregating both hardware and software layers, thereby simplifying the challenges posed by swarm robotics. Three types of Kobot robots were used in this study: Kobot-S (simulated), Kobot-W (wheeled), and Kobot-F (flying).

The use of Kobot robots across different platforms (simulated, wheeled, and flying) provided a comprehensive, yet flexible, experimental setup. This enabled us to thoroughly validate the efficacy of our novel range and bearing system under various conditions and scenarios, thereby demonstrating its versatility and reliability in swarm robotics applications.
Figure 5.1: a) Kobot-W is built for ground swarm application. b) Kobot-F is a micro-aerial vehicle swarm platform.

5.1.1 Kobot-W

The Kobot-W robots serve as our primary physical testing platform. These robots are equipped with differential drives and are designed for relatively high computational and perceptive tasks. The addition of our novel range and bearing system integrated two types of Time-of-Flight (ToF) sensors: VL53L1 and VL53L5. These were positioned on the top layer of the robot to ensure unobstructed sensing capabilities.

5.1.2 Kobot-F

Kobot-F robots extend our experimental setup into the aerial domain. The onboard resources were configured to include the same range and bearing system used in Kobot-W, ensuring consistency across different types of mobility. Kobot-F’s lightweight structure and rapid assembly mechanism proved advantageous for iterative testing.

5.1.3 Kobot-S

We employed the CoRe software architecture to handle both high-level behavior programming and low-level hardware interactions. Our custom range and bearing system was integrated into this architecture as a modular component, enabling easy substitution with virtual equivalents for simulation purposes. The Kobot-S simulation plat-
form allowed for initial behavior testing and validation, with the kinematic simulator mimicking real-world physics to a high degree of accuracy. These virtual robots were configured to simulate the behavior of our custom ToF sensor systems, providing a seamless transition from simulation to real-world scenarios[30].

5.2 Temporary VL53L5 Based Range and Bearing System

We encountered several challenges with the motherboard in developing the VL53L5-based range and bearing system. These issues are slated for resolution in future iterations. Given the time constraints, we opted for a simplified design to demonstrate the system’s performance in cluttered environments.

The revised motherboard features a single-layer PCB crafted using the copper milling technique. Our objective influenced this design change to streamline the development process. We selected the Pico developer board, equipped with an RP2040 microcontroller, to maintain consistency with the RP2040 already integrated into the motherboard. The Modbus protocol was chosen for communication with the robot due to its reliability and efficiency.

![Image of the temporary VL53L5 based range and bearing system](image)

Figure 5.2: The temporary version of VL53L5 based range and bearing system

These updated motherboards have been incorporated into the Kobot-W. This integration was crucial in creating a proof of concept for the VL53L5-based range and bearing system. A notable alteration in this design is the inclusion of only four VL53L5 sensors, a reduction from previous configurations. This modification was a strategic
decision to balance system complexity with performance requirements.

These developments represent a significant advancement in our project, showcasing our ability to adapt and innovate under tight deadlines while focusing on system functionality and performance in complex scenarios.

5.3 Polar Coordinate Control Mechanism

To characterize the performance of the RnB system, we built an experimental setup to control the relative pose \((d, \theta)\) of two MAVs equipped with the RnB system. We measured the actual values of the relative position variables using a Vicon motion capture system (Vicon Motion Systems Limited, Oxford, UK), and we synchronized this ground truth information with the readings collected using the RnB systems.

Figure 5.3: The polar coordinate control mechanism where all range and bearing performance tests were performed. The range and bearing system was connected to the Kobot-F and all data of the experiments were collected by the Vicon motion capture system.

5.4 Robot Arena

The robot experiments were conducted in an arena equipped with a Vicon motion capture system that detects ground and aerial robots with high precision. The data of
the experiments performed in the arena were recorded by a 360-degree Insta360 camera on the ceiling. The instantaneous data of the robots were synchronously recorded for later analysis through the ROS interface.

![Figure 5.4: The robot arena where all experiments were conducted.](image)

### 5.5 Self-Organized Flocking

A standard way to make robots act like a flock without central control is self-organized flocking (check out Algorithm). This is done using time-of-flight (ToF) sensors that measure distance and direction. The robots need to know how far and in which direction nearby objects are and figure out whether these objects are other robots or obstacles.

If an object is identified as an obstacle, the robot acts as if a make-believe force is pushing it away from that obstacle. The algorithm sets a target distance from obstacles as the maximum distance the sensor can detect. On the other hand, if the object is a neighboring robot, the algorithm acts as if there is a virtual spring connecting the two robots. The length of this spring is set to be less than the maximum distance the sensor can detect. This imaginary force between the two robots helps them avoid crashing into each other while keeping them close enough to act like a cohesive group.

Time-of-flight (ToF) range and bearing (RnB) systems are more accurate than other
infrared-based range and bearing systems. They also respond more evenly when measuring distances and directions. In this study, the force value $f_k$ is limited to be between -1 and 1. Because of this, we used a simple, straight-line method to create forces. This makes the robot’s movements around a balanced state more quick and smooth. So, the imaginary force used in the ToF RnB system is figured out by:

$$f_k = \frac{(\sigma - \sigma_{des})}{C}$$ \hspace{1cm} (5.1)

Note that the "C" value is different for robots and obstacles. In this way, the balance between the forces of robots and obstacles can be changed in the algorithm.

$$\vec{p} = \frac{1}{N} \left| \sum_{k=1}^{N} f_k \theta_k \right|$$ \hspace{1cm} (5.2)

In addition to this, the average heading of the flock can be found as follows:

$$\vec{h} = \frac{\sum_{j \in N} e^{i\theta_j}}{\left| \sum_{j \in N} e^{i\theta_j} \right|}$$ \hspace{1cm} (5.3)

Robot control can be calculated as:

$$\vec{a} = \frac{\vec{h} + \beta \vec{p}}{|\vec{h} + \beta \vec{p}|}$$ \hspace{1cm} (5.4)

Each robot can be expected to flock by moving under the influence of this force.
Algorithm 3: Self-Organized Flocking [1]

Data: Ranges: obstacle and robot range values from the RnB sensor
Headings: headings of the nearby robots from local communication

while true do
    \( \vec{p} = \text{get_vf}(\text{ranges}); \) // Resultant virtual force vector
    \( \vec{h} = \text{get_vh}(\text{headings}); \) // Resultant virtual heading vector
    \( \vec{a} = \vec{h} + \beta \vec{p}; \) // Desired heading vector
    \( e_h = \text{atan2}(\vec{a}_c) - \text{atan2}(\vec{a}); \)
    \( \omega = K_p \times e_h; \)
    if \( |e_h| < \frac{\pi}{2} \) then
        \( u = (\vec{a} \cdot \vec{a}_c) \gamma u_{\max}; \)
    else
        \( u = 0; \)
        go(u, \omega);
CHAPTER 6

RESULTS AND DISCUSSION

In Chapters 3 and 4, we discussed the design and important calculations for range and bearing systems. The next step is to test these theoretical concepts through practical experiments. This chapter focuses on evaluating the performance of two distinct range and bearing systems under different conditions.

Firstly, we examine the system based on the VL53L1 ToF sensor. Our tests cover two main areas: the accuracy of distance measurement (ranging) and the system’s ability to detect robots. These experiments are essential to determine how well this system performs in real-world conditions and its effectiveness in a swarm robotics setting.

For the system that uses the VL53L5 sensor, our approach differs due to hardware limitations. Instead of a swarm scenario, we evaluate its performance in a cluttered environment. This test focuses on the system’s ranging accuracy and robot detection capabilities, particularly how well it functions amidst various obstacles and distractions. This is a crucial aspect of performance, as it simulates the complex environments where swarm robots often operate.

Although we couldn’t test the VL53L5-based system in a swarm scenario, the cluttered environment test still provides valuable insights into its effectiveness and potential applications in real-world situations.

6.1 VL53L1 Based Range and Bearing System

In this section, we focus on evaluating the performance of the range and bearing system that utilizes the VL53L1 Time-of-Flight (ToF) sensor, as previously described.
The experiments are conducted using Kobot robots and the polar coordinate mecha-
nism outlined in the experimental setup.

Our first goal is to determine the system’s operational limits. This involves testing
the range and accuracy of the VL53L1 sensor under various conditions to establish
its boundaries and capabilities.

Lastly, as a proof of concept, we demonstrate flocking behavior using five Micro
Aerial Vehicles (MAVs) equipped with the Range and Bearing (RnB) system. This
test aims to showcase the practical application of the system in a coordinated swarm
operation, highlighting its effectiveness in real-world scenarios.

### 6.1.1 System Limits

In earlier sections, we based our system design on data from the Time-of-Flight (ToF)
sensor’s datasheet. However, it’s important to remember that these specifications
are often derived from tests in ideal conditions. For our range and bearing system,
especially when used with robots that have a small radar cross-sectional area like
micro-aerial vehicles, it’s crucial to verify this data in more realistic settings.

We’ve already discussed some methods to address these potential discrepancies. Now,
in this section, we test these solutions and explore the actual limitations of the sys-
tem. We aim to see how well our system performs in real-world conditions and to
understand its boundaries.

#### 6.1.1.1 Effectiveness of Retro-Reflective Folio Coating

This experiment aims to investigate the effect of a reflective coating reflecting IR light
on the RnB measurements. For this purpose, two MAVs equipped with the same RnB
system are placed opposite each other in the experimental setup. One of the MAVs
is covered with reflective coating while the other is not. The ground-truth data of
the robots in the experimental setup is collected by the Vicon motion capture system.
Figure 6.1 shows how accurately the robots with and without the reflective coating
are detected.
IR reflective coating increases the reflection of IR light. Since it increases the threshold in the measurements of the sensor, IR reflective foil-coated robots can be perceived as robots with a much higher cross-section. Thanks to the coating, we can see that the measurements become more accurate and measurements can be made even after 700mm. It has contributed to the system being able to work especially in MAVs.

### 6.1.1.2 Effectiveness of Robot Detection Methods

The IR signals are collected while the sensor does not measure distance, and are called *ambient* signals. We have explained in previous sections how the sensor measures distance and identifies neighboring robots. In this experiment, the effect of random delay, which is the most important component of the robot detection algorithm, on robot detection is investigated. Two MAVs equipped with range and bearings, placed in \( d = 650 \text{ mm}, \theta = 0 \) in the experimental setup, were kept stationary throughout the experiment. Figure 6.2a shows *ambient*, *range*, and *isRobot* values for both range bearings without using random delay. Figure 6.2b shows the change of the same metrics after adding random delay to the robot detection algorithm.
Figure 6.2: Plots representing ambient reading range error and robot detection metrics a) without random delay b) with random delay.

Figure 6.2-a shows the periodic interference in the measurements before the random delay is added. As a result of this overlap, the ambient signal readings increase periodically at certain intervals. This increase also triggers errors in the range measurement. This periodic interference causes the ambient measurement to be sometimes too low and sometimes too high. The robot detection algorithm, which is based on the fluctuation of the ambient signal, has problems. These problems can be solved by enlarging the robot detection buffers. However, doing this causes the system to slow down the robot detection algorithm. Adding the random delay mentioned in previous chapters allows the measurements of the two sensors to affect each other at more random times. In this way, we have a continuously fluctuating ambient signal. This simply makes it easier and faster to sense the robot. When Figure 6.2-b is analyzed, the increase in the fluctuation in the ambient helps the robot detection algorithm to work more accurately. The interesting point is that there are also improvements in the distance measurement in Figure 6.2-b. We have already mentioned that a high ambient signal negatively affects the distance measurement. However, low ambient readings from fluctuating ambient signals due to random delay are still reliable for distance measurements. In the buffer in the distance measurement, more reliable range data with lower ambient readings are stored and processed. In this
way, the random delay contributes positively to robot detection and ranging.

6.1.1.3 Performance of system in working area

In this experiment, the directly simultaneous measurement capability of the range and bearing sensor is investigated. Two MAVs equipped with range and bearing sensors were tested in the harshest conditions in the experimental setup. These conditions are \( d = [0\ mm, 1300\ mm] \) up to the maximum distance measuring capacity of the sensor. Using the symmetricity of the sensor, \( \theta = [0^\circ, 15^\circ] \), which is half of the angle difference between the two sensors, was chosen for the target bearing angle. Ground-truth data was collected by the Vicon motion capture system throughout the entire experiment. The real data in this experiment, which was repeated 5 times, were placed on the polar plot shown in Figure 6.3 as \( d \) and \( \theta \). Each position in the polar plot shows the ranging error between the sensor measurement and the ground-truth data at that point.

![Polar plot showing range error](image)

Figure 6.3: Color-mapped polar plot representing range error of RnB with respect to changing inter robot distance \( d \) and angle \( \theta \)

Figure 6.3 shows the performance in the area that the sensor should see according to the hardware design. According to the sensor data, although the sensor is capable of sensing 13.5 (Half of full FoV 27 degrees) degrees, it is only able to see up to 800mm in the entire region. The most important reason for this is the cross-section of the range and bearing system and the robot system equipped with it. We would expect the range and bearing’s distance performance to increase as the robot being sensed becomes larger. In addition, robots may perform worse near the sensor’s mea-
surement limit. We see a higher ranging error between $200 - 400$ mm and between $1000 - 1300$ mm. Nevertheless, even in these regions, no errors larger than a maximum of 50mm were made. These results can be considered sufficient for an onboard measurement in MAVs. We can already observe the effect of this error rate on inter-robot distance control when investigating the swarm performance of the system. The system’s ability to completely sense obstacles closer than 800 mm allows the robots to move without collisions.

6.1.2 Swarm Scenario

Some experiments were carried out to prove that the range and bearing system works well with swarm robots. These experiments were first performed in a simulator environment and then supported with real robot experiments.

6.1.2.1 Self-Organized Flocking with Kobot-F

The self-organized flocking algorithm was used to test the performance of the range and bearing system in swarm settings\[31\]. In these experiments, five Kobot-Fs achieved flocking with onboard sensing and onboard computation. The results of the experiment were synchronously collected by a Vicon motion capture system.

Two flocking metrics can be used to measure the swarm setting success of the range and bearing system. The first one, angular order ($\psi$), measures how close the orientations of the robots in the flock are to the orientation of the flock they belong to. Angular order can be defined as follows:

$$\psi(t) = \frac{1}{N} \left\| \sum_{k=1}^{N} e^{i\theta_k} \right\|$$

$\theta$ symbolises the heading of the $k^{th}$ robot. Angular order($\psi$) $\rightarrow 1$, indicates that the flock is perfectly aligned, while Angular order($\psi$) $\rightarrow 0$, indicates that the robots are randomly aligned. The other metric is the Mean Inter-robot Distance (MID). This metric is found by averaging the distance between robots that sense each other. MID,
which is recalculated for each moment, shows how well the robots can maintain the
distance between each other. A value of MID around $\sigma_{des}$ indicates that the robots
in the flock are not separated but stay together. When MID $\rightarrow 0$, it means that the
probability of collision within the flock is high, and when MID $\rightarrow +1300$, it means
that the robots in the flock are likely to break away.

Figure 6.4: Snapshots from self-organized flocking experiment with five Kobot-F
MAVs

This experiment carried out with 5 MAVs, was recorded with a 360-degree angle
camera placed above the flight arena. The video of this experiment can be watched
online. Figure 6.4 shows the snapshots taken during this experiment. In these shots,
the movement of the flock together can be observed.

The angular order metric was analyzed to investigate the orientation of the five MAVs
during flocking. The angular order metric obtained during the experiment is shown
in Figure 6.8.

The angular order metric is the most important metric that shows that the robots in
a swarm have the same orientation. It is known that for many robots that use global
sensing systems, this metric converges to 1. However, for systems with discrete nature such as range and bearing, we can say that it is acceptable for the angular order to be in the range of $0.8 - 1.0$. We can say that our system is in this range for most of the plot. However, there are a few times in the Figure where there are large drops. In particular, it can be seen that the angular order($\psi$) drops to 0.4 for a moment. There are two main reasons for this. The first reason is the algorithm we implemented. In many migration-based flocking algorithms, one of the main components that determine the direction of the swarm is the migration velocity. However, in self-organized flocking, the desired heading of the flock is found by averaging the heading of the robots in the flock. As a result, there is a very chaotic situation, especially when the whole flock bounces off long obstacles such as walls. We know that these instantaneous drops in the graph come at the moments of the flock’s return from the obstacle. Another reason for the sudden deterioration in the angular order is that the experiments were performed with micro-aerial vehicles, the most challenging swarm robot. We have mentioned in previous chapters that range and bearing work in a 2.5D environment. Especially around large obstacles such as walls, the airflow is very disturbed, making it difficult for MAVs to maintain constant heights. There are moments when robots cannot sense neighboring robots that fly around them. With this bad effect on long obstacles, there are large decreases in angular order.
Figure 6.6: Figure showing mean inter-robot distance among 5 MAVs. Red-line represents the desired distance between robots.

The mean of the inter-robot distances (MID) measured by the five MAVs during the experiment was plotted against time. Also, the desired distance between the swarm robots during the experiment is plotted.

We can say that "MID" oscillates around the desired distance during the experiment. It can be said that this result is sufficient in systems such as flocking where multiple robots are controlled in a decentralised manner. In cases where robots squeeze each other due to obstacles, the mean inter-robot distance is expected to decrease and the system is expected to expand with the forces generated after this squeeze. In addition, we encounter a lot of noise in the data. The main reason for this is the reading disturbances due to the height differences of the RnB systems and the intense noise in the swarm setting.

6.2 VL53L5 Based Range and Bearing System

We extensively tested the VL53L1 sensor-based range and bearing system in the preceding section to understand its limitations. The results from these experiments revealed that the sensor’s performance closely aligns with the specifications detailed in
its datasheet, particularly when used in swarm robotics. An important takeaway was the effectiveness of covering swarm robots with reflective foil, which proved beneficial for infrared-based range and bearing systems.

Building upon these insights, we applied the experiences learned to develop the VL53L5-based range and bearing system. The VL53L5 sensors share a technological similarity with the VL53L1, but with an added advantage: their geometric arrangement on the motherboard eliminates blind zones. This key improvement obviated the need for extensive testing of system limits, as seen with the VL53L1.

Instead, we tested how well the VL53L5 system works with multiple robots. It’s important to mention that these tests were done using a temporary version of the motherboard because there were some problems with the first system we developed. Even though this was not ideal, these tests were really important. They helped us see how good the system is in real situations where many robots work together. These tests taught us a lot about what the system can do and what we might need to improve in the future.

### 6.2.1 Obstacle Avoidance with Kobot-W

In this particular experiment, our objective was to evaluate the performance of the VL53L5 ToF-based range and bearing system in environments densely populated with obstacles. To achieve this, we employed a search-based flocking algorithm[32], a method previously established. This algorithm, while primarily designed to enable multiple robots to move together in a unified direction, also possesses the capability to facilitate obstacle avoidance for individual robots.

Throughout the experiment, the robot’s direction or migration vector was guided by readings from its magnetometer. Importantly, the detection of obstacles relied solely on the range and bearing readings from the VL53L5 system. It’s worth noting that the robot’s onboard camera and the top-view camera images used in the experimental snapshots and videos were incorporated solely for illustrative purposes. These visual aids were intended to enhance the comprehension of the experiment’s setup and progression; they played no role in the actual obstacle detection process.
A critical outcome of these tests was that the robot successfully navigated the cluttered environment without collisions. This result not only underscores the effectiveness of the implemented algorithm but also demonstrates the VL53L5 RnB system’s ability to promptly and accurately detect obstacles. The seamless integration of the range and bearing system with the robot’s control mechanisms contributed significantly to this successful navigation, highlighting the system’s potential in real-world applications where obstacle-rich environments are common.

Figure 6.7: Snapshots from obstacle avoidance experiment

6.2.2 Cluttered Environment Test with Kobot-W

In a recent experiment, we evaluated the performance of the VL53L5 sensor in a cluttered environment featuring a mix of robots and various obstacles. The primary aim of this test was not to generate numerical data but to gain a qualitative understanding of how the range and bearing system functions in complex, obstacle-rich settings.

For this experiment, the robot, equipped with the VL53L5-based RnB system and an onboard camera, was manually maneuvered by an operator. Real-time video footage was captured from above the experimental area to provide a comprehensive perspective of the robot’s navigation.

The setup included a variety of obstacles: long barriers mimicking walls, shorter obstacles, and others comparable in size to the robots. Snapshots taken during these trials and videos of the experiments are available for detailed observation. These visual records are particularly useful for understanding the system’s interaction with different types of obstacles and the robot’s movement patterns.

A significant finding from this experiment was that all estimations made by the robot
regarding the location and distance of other robots in the environment were accurate. This outcome underscores the precision and reliability of the VL53L5 sensor in detecting and measuring distances to other robots, even in a cluttered environment. However, it was also observed that the system occasionally misread readings from the ground as obstacles. This suggests further refining the system’s operational parameters or algorithm to enhance its distinction between ground surfaces and genuine obstacles.

The experiment provided valuable insights into the sensor’s detection capacity and operating logic. The visual documentation of these tests also offers a clear demonstration of the system’s efficiency and reliability in real-world scenarios that resemble cluttered environments.
This thesis presents two novel time-of-flight sensor-based range and bearing systems. These systems allow swarm robots to operate in a cluttered environment with on-board resources. The system performs real-time relative localization while distinguishing between robots and obstacles. This system, which is highly modular and equipped with known communication systems (I2C, SPI), can be easily integrated into all robots. Considering its size and weight, it is suitable for tiny mobile robots and even micro aerial vehicles.

In this study, the hardware design of RnB systems, the software that enables them to work even in the very noisy environment created by swarm robots, and the multi-target tracker module that tracks neighboring robots and estimates their states are discussed. Experiments were conducted to measure the success of these subsystems. Real robot experiments were conducted to validate our concept thanks to the confidence gained from the sub-system experiments. Self-organized flocking was implemented with five Kobot-F equipped with VL53L1-based range and bearing system and its success was investigated. Due to hardware problems, the VL53L5-based range and bearing system was tested in a cluttered environment.

This study can proceed in several different ways from now on. The most important one is using machine learning methods. As explained in the previous sections, using eight sensors, which measure in 64 separate zones, actually creates low-resolution images. In addition to range measurement, the sensor provides data such as ambient, sigma estimator, reflective ratio, etc. Processing them with tiny machine learning algorithms which can run on microcontrollers, will boost the relative localization performance. Secondly, the ToF sensors are very sensitive to sunlight. Saving the
system from the destructive effect of sunlight will have a positive impact on outdoor swarm robots. Last but not least, this system could be combined with other range and bearing systems. In particular, the combination of an easy-to-use mono camera, which is available in most of swarm robots, opens the way to be used in other algorithms such as foraging. I believe that future studies in these areas will make important contributions to the literature.
REFERENCES


