Smart Traps for Precision Agriculture: Innovative Detection of Mediterranean Fruit Flies Using Sensor Integration.

Por:

M.C. Miguel Hernández Rosas

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Supervisada por:

Leopoldo Altamirano Robles
Guillermo Espinosa Flores-Verdad
Hayde Peregrina Barreto

Resumen

La agricultura juega un papel importante en el crecimiento económico. En este contexto; México alcanzo en 2020, 23,495 MDD en exportaciones agroalimentarias; superando así las conseguidas por remesas (673 MDD), venta de productos petroleros (14,047 MDD) y turismo extranjero (16,474 MDD) [6]. Lo alcanzando en 2020 representan el valor más alto reportado en 28 años (desde 1993).

Es por ello que el rendimiento de los cultivos tiene un gran impacto en la economía del país. Sin embargo, uno de los problemas más graves a los que se enfrenta la agricultura son las plagas de insectos, pues afectan los procesos metabólicos de los cultivos al degradar su rendimiento y calidad; lo que puede obstaculizar aún más el desarrollo de la agricultura [60].

De entre la amplia variedad de plagas se encuentra la mosca mediterráneo (*ceratitis capitata*), una de las más relevantes debido al impacto económico que ha causado en los cultivos frutales de todo el mundo. En ausencia de control, la mosca del mediterráneo puede llegar a dañar hasta el 100% de un cultivo [14]. El daño principal ocurre cuando las hembras ovispan en los frutos y; una vez que eclosionan, las larvas inician su alimentación, facilitando así el desarrollo de microorganismos que contribuyen a un mayor colapso del fruto [51].

Para esta y otras plagas, el monitoreo con trampas es un componente común y crítico en los programas de detección, delimitación, supresión y erradicación de plagas en todo el mundo. En el caso de las moscas del mediterráneo, los dispositivos de captura están basados en estímulos específicos olfativos y/o visuales para atraer a los adultos de la especie. La mayoría de los atrayentes utilizados por las trampas son de tipo alimenticio, las cuales liberan amoniaco y simulan fuentes de proteínas [51].

Sin embargo, el costo de mantenimiento de una red de trampas es bastante alto si se considera los recursos monetarios, humanos y materiales que se requieren para mantener un red de trampas. El mantenimiento de la red no solo se limita

a la diseminación de trampas, sino también la frecuencia con la que se controla y recolecta su información [14]. Por lo que este proceso puede llegar a ser complejo en el mantenimiento y recolección de datos. Aunado a lo anterior, se debe tener en cuenta el tiempo necesario para analizar las especies capturadas, ya que la información sobre las especies y densidades de plagas se adquiere principalmente a través de la inspección visual (forma, color, textura, entre otros) [40, 60].

Las trampas de monitoreo automático (*smart traps*) ayudan a resolver los problemas anteriormente planteados y son eficientes; ya que pueden identificar y contar a la plaga a medida que ingresan a la trampa [60], lo cual permite un flujo de información más rápido.

El presente trabajo muestra la implementación de un trampa inteligente diferente y novedosa a los enfoques reportados al día de hoy en la academia e industria. La propuesta está basada en la utilización de la fusión de sensores para la identificación de la plaga.

Abstract

Agriculture plays an important role in economic growth. in this context; Mexico reached in 2020, 23,495 million dollars in agri-food exports; thus exceeding those achieved by remittances (673 million dollars), sale of oil products (14,047 million dollars) and foreign tourism (16,474 million dollars) [6]. reaching it in 2020 represent the highest value reported in 28 years (since 1993).

That is why crop yields have a great impact on the country's economy. however, one of the most serious problems facing agriculture are insect pests, since they affect the metabolic processes of crops by degrading their yield and quality; which may further hinder the development of agriculture [60].

Among the wide variety of pests is the Mediterranean fly (*ceratitis capitata*), one of the most relevant due to the economic impact it has caused on fruit crops around the world. In the absence of control, the Mediterranean fly can damage up to 100% of a crop [14]. the main damage occurs when the females ovistop on the fruits and; once they hatch, the larvae begin to feed, thus facilitating the development of microorganisms that contribute to further fruit collapse [51].

For this and other pests, trap monitoring is a common and critical component in pest detection, delimitation, suppression and eradication programs around the world. In the case of Medflies, the capture devices are based on specific olfactory and/or visual stimuli to attract the adults of the species. most of the attractants used by the traps are food-type, which release ammonia and simulate protein sources [51].

However, the cost of maintaining a trap network is quite high considering the monetary, human, and material resources required to maintain a trap network. Network maintenance is not only limited to the spread of cheats, but also the frequency with which your information is monitored and collected [14]. Therefore, this process can become complex in the maintenance and collection of data. In addition to the above, the time necessary to analyze the captured species must

be taken into account, since the information on the species and pest densities is acquired mainly through visual inspection (shape, color, texture, among others) [40, 60].

Automatic monitoring traps (*smart traps*) help to solve the previously mentioned problems and are efficient; since they can identify and count the pest as they enter the trap [60], which allows for a faster flow of information.

This work shows the implementation of a different and novel smart trap from the approaches reported to date in academia and industry. the proposal is based on the use of sensor fusion to identify the pest.

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This thesis is as much yours as it is mine. Thank you for being my partner in every sense of the word, and for the beautiful future we are about to embark on together.

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Chapter 1

Introduction

1.1 Background and Importance of Monitoring Mediterranean Fruit Flies

Agriculture plays an important role in economic growth. Mexico reached 23,495 million dollars in agri-food exports in 2020; thus surpassing those achieved by remittances (673 million dollars), sale of oil products (14,047 million dollars) and foreign tourism (16,474 million dollars) [6]. This represents the highest value reported in 28 years (since 1993) as you can see from Figure 1.1.

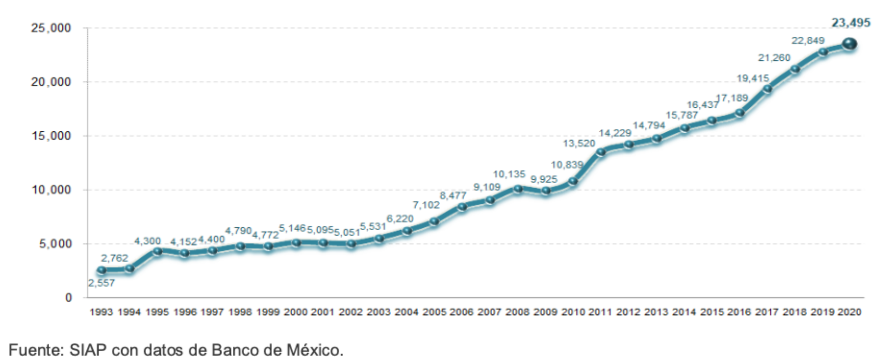


Figure 1.1: Evolution of Mexican agri-food exports, January-July 1993-2020 (MDD).

From Figure 1.1, it follows that improving crop yields is of great importance. However, insect pests affect the metabolic processes of crops by degrading the performance and quality of these, which can further hinder the development of the agriculture.

In general, pests can be managed using pesticides, the effectiveness of which largely depends on timely and accurate detection of infestations. However, pesticides not only impact the natural enemies of pests but also beneficial pollinators. Additionally, they can contaminate water sources and pose significant risks to human health [60].

Among the wide variety of pests is the Mediterranean fly (*ceratitis capitata*); which is one of the main ones due to the economic impact it can cause in the fruit crops from around the world. In the absence of control, the Mediterranean fly could damage up to 100% of a crop [14]. The main damage occurs when females ovist in the fruits and; Once they hatch, the larvae begin their feeding, thus facilitating the development of microorganisms that contribute to greater collapse of the fruit or crop [51].

For the special case of Mexico, the condition it maintains is free of the Mediterranean fly; this thanks to the *Moscamed México Program* that has been applied since 1978. This program has the The objective is to eradicate and contain the Mediterranean fly using different measures such as:

- detection by trapping of adult flies with sexual pheromones and food attractants;
- detection by fruit sampling;
- autocidal control (release of sterile flies);
- control biological (experimental, through the augmentative release of parasitoids);
- mechanical control and cultural;
- chemical control by spraying insecticide baits;
- legal control, and
- relations public and dissemination [49].

Among the benefits of the program is access to fruits and vegetables that Mexico It exports to countries such as the United States and Japan, among others, which have the most attractive markets for Mexican exporters of dozens of fruit and vegetable products. This benefit has also been quantified from 1978 to 2008 in [49], resulting in:

- Direct benefits, represented by the volume and net value of production and exports of fruits and vegetables that amounted to **40,555** and **25,866 million dollars** during the analysis period; while the indirect ones reached 19,593 million dollars.
- In the event that the Mexican government had not implemented a control program; he could have saved the amount invested; however, there would have been losses potential for **4,237 million dollars** in the production of fruits and vegetables susceptible to being attacked by the Mediterranean fly, given the very possible infestation of the pest and the consequent amounts of insecticide that would have had to be applied.
- In addition to the above, **25,866 million dollars** are added for the value net of exports that had ceased to take place during the period.
- **17,527 million dollars** of indirect impacts must also be considered (in health of the rural population, creation and maintenance of employment in the fruit and vegetable activity, and environmental damage) for not having an integrated strategy to control the plague.

In contrast to these data, in 2015 the Brazilian Ministry of Agriculture reported that the fly of the Mediterranean had caused annual losses of **120 million dollars** to the producers; between production losses and control costs. Stopping exporting to the markets from Japan, the United States and Chile [40]. Although this program and many others for different pest species have demonstrated good results, the different activities developed for the comprehensive management of the pest present challenges. This is why an innovative and sustainable pest management strategy is required. [29].

1.2 Precision Agriculture and Integrated Pest Management

Precision agriculture and Integrated Pest Management (IPM) represent two pivotal aspects of modern agricultural practices aimed at enhancing sustainability and productivity. By integrating these strategies, farmers can achieve more precise control over agricultural inputs, optimize crop health, and reduce environmental impacts.

Precision agriculture utilizes advanced technologies to make farming more accurate and controlled. GPS technology, drones, satellite imagery, and sensor technology are among the tools that enable precise monitoring and management of crop health and soil conditions. This approach allows farmers to apply water, fertilizers, and pesticides more efficiently, reducing waste and enhancing crop yields.

The cornerstone of precision agriculture lies in its data-driven methodology. Farmers use detailed data collected from their fields to analyze everything from soil moisture levels to nutrient status and pest infestations. This information helps in making informed decisions about when and where to irrigate, plant, fertilize, and apply pest control measures. The result is a highly efficient farming operation that maximizes output while minimizing unnecessary expenditure and environmental impact.

The Integrated Pest Management (IPM) is a holistic approach to sustainable pest control that combines biological, cultural, physical, and chemical tools in a way that minimizes economic, health, and environmental risks. IPM focuses on long-term prevention of pests or their damage through a combination of techniques such as habitat manipulation, biological control, use of resistant varieties, and appropriate chemical interventions.

The strength of IPM lies in its emphasis on understanding the ecological relationships within agricultural systems. By monitoring pest populations and their life cycles, farmers can implement targeted interventions that are effective yet less disruptive to the ecosystem. For instance, the introduction of natural predators to control a pest population, crop rotation to disrupt pest breeding cycles, and selective pesticides that do not harm beneficial insects are all IPM strategies that contribute to sustainable crop production.

The synergy between precision agriculture and IPM lead to revolutionary changes in agricultural practices. Precision agriculture provides the tools to accurately assess and manage field variability in factors such as soil fertility, moisture levels, and pest distribution. This precision, in turn, enhances the efficacy of IPM strategies by ensuring that interventions are applied optimally to achieve the best outcomes.

While the integration of precision agriculture and IPM offers numerous benefits, it also presents challenges. The high cost of technology and the need for specialized knowledge to interpret data and implement strategies can be barriers to adoption, particularly for smallholder farmers. However, ongoing advancements in technology and increased support from government and industry can help overcome these hurdles.

As we move forward, the convergence of precision agriculture and IPM is set to redefine farming practices. This integration not only aims to increase efficiency and yields but also prioritizes environmental stewardship and the health of the agricultural ecosystem. By continuing to develop and refine these approaches, the future of agriculture looks both sustainable and prosperous, ensuring food security and ecological balance for generations to come.

1.3 Objectives and scope of the thesis literature review

The escalating challenges in agricultural pest management demand innovative solutions to ensure crop health and productivity. Traditional methods often fall short in providing timely and precise pest detection, leading to significant economic losses and environmental damage due to over-application of pesticides. This thesis explores the integration of advanced technologies to develop a more accurate, efficient, and environmentally friendly approach to pest detection in crop management.

1.3.1 Objectives

The primary objective of this thesis is to design and evaluate a crop pest detection system that leverages the capabilities of sensor fusion and image processing. The specific goals are outlined as follows:

- Develop a comprehensive understanding of the current state of pest detection technologies:
  - Review existing methods and technologies in pest detection, focusing on their advantages, limitations, and applicability for de Mediterranean fruit fly.
  - Identify gaps in current technologies that could be bridged by interation of new sensor technologies and image processing algorithms.
- Design an integrated pest detection system using sensor fusion:

  - Integrate different sensors to collect diverse data types that can provide a multifaceted view of pest presence.
  - Utilize sensor fusion techniques to combine data from different sources, enhancing the robustness and accuracy of the pest detection process.

- Implement image processing algorithms to identify and classify crop pests.

- Validate the system in a controlled environment settings:

  - Conduct experiments in controlled settings to fine-tune the system and ensure its functionality for field conditions.
  - Test the system to evaluate its practicality, accuracy, and efficiency for trap monitoring.

1.3.2 Scope

The scope of this thesis encompasses several key areas:

- Technological Integration. The study focuses on integrating multiple sensing technologies and image processing techniques to create a unified system for early and accurate pest detection for Meditteranean fruit flies.

- Algorithm Development. Central to the thesis is the development of robust algorithms that can process and analyze data from diverse sensors and images to detect and classify Mediterranean fruit between other species captured in traps.

- Field Trials. The system will be tested in a first stage in controlled settings to ensure its applicability and effectiveness across various scenarios.

- Impact Analysis. The research will include a detailed analysis of the system's impact on reducing trap visitation frequency, improving pest detection accuracy, and enhancing overall human labor.

- Limitations. The study will acknowledge the limitations of the proposed system, including technical constraints, environmental factors, and potential challenges in real-world implementation.

This research aims to make significant contributions by developing a smart trap system that incorporates software, hardware, and mechanical components for effective field operation. The project also focuses on devising a methodology for a radar system that employs a novel approach to detect the Mediterranean fruit fly. Additionally, it includes the integration of air quality sensors to monitor the presence of lures, thereby reducing the need for frequent physical inspections of traps and lowering associated maintenance costs. Ultimately, the construction of this system is designed to provide robust infrastructure, reduce operational costs, and enhance the productivity of Ecosur in monitoring the Mediterranean fruit fly.

1.4 Objectives and scope of the thesis

1.4.1 Research Questions

1. What kind of *smart trap* design can achieve efficient communication for continuous monitoring of the *Mediterranean fly* while maintaining a cost-performance ratio suitable for use in networks of traps?

2. Which sensors provide the most relevant information to detect the *Mediterranean fly*?

1.4.2 Hypothesis

A smart trap based on the combination of millimeter-wave radar sensors (*mmWave radar data*) and computer vision could offer the necessary qualities to monitor pests remotely. Combined with an automatic recognition and classification system, efficient identification of pests in real-time would be possible.

1.4.3 Thesis

This work aims to design and develop a smart trap based on the combination of camera and radar sensors. The system development includes software, hardware, and mechanical design. The developed system will be tested with the help of *Centro de Empaque de Moscas del Mediterráneo* of SENASICA and Ecosur to validate its correct operation and functionality.

1.4.4 Contribution

This research aims to contribute by developing a smart trap with the necessary software, hardware, and mechanical components for a functional system that operates in the field. It also seeks to develop a methodology for combining radar and camera sensors and a new automatic classification system for identifying the Mediterranean fly using a novel sensor-based approach. Ultimately, the construction of this system aims to provide infrastructure, reduce costs, and increase the productivity of Ecosur for monitoring the Mediterranean fly.

1.4.5 General Objective

- Design and implement a digital smart trap system based on the combination of camera, radar, and other sensors for automatic real-time and remote monitoring of the Mediterranean fly.

1.4.6 Specific Objectives

- Design the software, hardware, and mechanical components necessary to implement a *smart trap* system.

- Propose a combination scheme of camera, radar, and other sensors to develop an automatic classification scheme for the Mediterranean fly.

- Validate the system's operation and functionality in conjunction with Ecosur.

1.5 Thesis outline

The outline of this thesis begins with an introduction that establishes the background and importance of monitoring the Mediterranean fruit fly, followed by a discussion on the concepts of precision agriculture and integrated pest management. This sets the stage for understanding the technological and methodological innovations introduced in the subsequent sections.

The literature review provides a comprehensive analysis of conventional traps and monitoring techniques, followed by a detailed exploration of smart traps and recent technological advancements. This section also delves into the various sensors and detection mechanisms that have been utilized in entomology, with a particular focus on radar technology.

In the materials and methods section, the design and development of the smart delta trap are elaborated. This includes the main body and structure, ventilation and accessibility, top panel and sensor integration, assembly and electronics housing, and structural reinforcements. Each component is meticulously described to illustrate the integrated approach used in developing the trap.

The description of sensors and radar systems used in the smart delta trap follows, detailing the camera sensor, temperature, humidity, and pressure sensors, air quality sensors, color sensor, RTC sensor, radar sensor, and WiFi. This section explains the selection criteria and functionalities of each sensor, providing a clear understanding of their roles within the system.

The trap configuration and experimental setup section outlines the procedures followed to test and validate the smart delta trap. This includes the experimental design, setup, and the conditions under which the tests were conducted.

The development of the smart delta trap is discussed next, with a focus on design considerations and challenges. This section covers the requirements, component determination, sensor integration, and hardware implementation. The software development for data analysis is also detailed, describing the system and architecture design for the system on chip (SoC), application architecture, system architecture design and management, and the structural model of the software system.

The results and analysis section presents the findings from the radar-based detection and counting of fruit flies. This includes the materials and methods used, and the results obtained. The performance of various sensors, such as TVOC and eCO2 detection, is evaluated in this section, highlighting the efficacy and accuracy of the sensors used in the smart trap.

A comparison with traditional monitoring methods is provided to contextualize the advancements and improvements offered by the smart delta trap. This section discusses the advantages and limitations of the developed trap, providing a balanced view of its performance and potential areas for improvement.

The thesis concludes with a discussion on potential improvements and future work. This section outlines the possible enhancements that can be made to the smart delta trap, and the future research directions that could be pursued to further refine and optimize the system.

The thesis outlines the development, implementation, and validation of a smart delta trap for the Mediterranean fruit fly. The comprehensive approach taken in integrating various sensors and developing robust software for data analysis demonstrates the potential of advanced technologies in improving pest monitoring and management practices.

Chapter 2

Literature review

2.1 Conventional traps and monitoring techniques

Several traps and monitoring techniques are commonly employed to detect and manage infestations of the Mediterranean fruit fly, *Ceratitis capitata*. The Jackson trap, specifically designed for this purpose, is highly effective in attracting and capturing adult Mediterranean fruit flies. Additionally, McPhail traps, typically made of glass or plastic, utilize a liquid protein bait to attract fruit flies and are effective for both monitoring and controlling fruit fly populations [54].

Visual inspections and field surveys are also integral in assessing infestation levels and evaluating the effectiveness of management strategies. To enhance the efficacy of these traps, chemical lures such as methyl eugenol and cuelure are used. These substances specifically target fruit fly populations, aiding in their management[54].

Another significant method within broader control strategies is the Sterile Insect Technique (SIT), where sterile flies are released to mate with female flies. This interaction results in no offspring, contributing to a reduction in the pest population over time. Collectively, these methods comprise a comprehensive approach to monitoring and managing the Mediterranean fruit fly. By combining mechanical trapping with biological control strategies, these methods effectively assess and mitigate the impact of this pest on agricultural operations [54].

According to Montoya [39], the traps used to monitor and control the Mediterranean fruit fly in Mexico include various types summarized in Table 2.1. These traps, used with different monitoring techniques and attractants, detect and control the presence of fruit flies in the field. For example, the Fly/Trap/Day (FTD)

Index is used to estimate the relative abundance of fruit fly populations. Factors influencing FTD include abiotic conditions (temperature, humidity, rainfall), biotic conditions (host plant type, density, phenology), physiological aspects of the fly (age, nutritional, and reproductive status), and the quality of traps. Preventive trapping is used in pest-free areas to detect fruit flies early and minimize the risk of introduction and spread. Delimitation trapping is applied once a pest has been detected to establish the boundaries of its spread. Monitoring trapping is used in infested areas to determine the presence and density of fruit fly species relative to the phenology of host plants, predicting future pest movements [39].

Besides the techniques and traps mentioned above, various attractants are used in Mexico. For example, *Trimedlure* (TML) is specific for male Mediterranean fruit flies, *Methyl Eugenol* (ME) is used for various *Bactrocera* species, and *Cuelure* (CUE) is effective for Bactrocera and *Zeugodacus* species. Hydrolyzed proteins are effective but less selective and used for general monitoring of fruit flies. Synthetic baits (*Biolure*), a combination of ammonium acetate (AA), putrescine (Pt), and trimethylamine (TMA), are used for detecting female Mediterranean fruit flies [39]. It is important to highlight that Trimedlure is the most effective attractant for the Mediterranean fruit fly and is a key component of the program *MoscaMed* for the majority of traps used in Mexico [39].

Research continues to develop more effective and specific attractants and trap designs, including the automation of traps for real-time monitoring to reduce labor costs and improve monitoring efficiency. These methods and tools are critical for the effective detection and control of Mediterranean fruit flies and other fruit fly species in Mexico.

Trap Name	**Type**	**Attractant(s)**	**Usage**
Jackson Trap	Dry-sticky trap	Trimedlure (TML)	Specific for capturing Mediterranean fruit fly (*Ceratitis capitata*)
McPhail Trap	Wet trap	Hydrolyzed protein, Torula yeast	General for *Anastrepha* species
Multilure Trap	Wet trap	Hydrolyzed protein, Torula yeast, Ammonium acetate (AA), Putrescine (Pt)	General for *Anastrepha* species

Trap Name	**Type**	**Attractant(s)**	**Usage**
Yellow Panel Trap	Dry trap with adhesive	Trimedlure (TML)	Specific for Mediterranean fruit fly (*Ceratitis capitata*)
C&C Trap (Cook & Cunningham)	Dry trap with adhesive	Trimedlure (TML)	Specific for Mediterranean fruit fly (*Ceratitis capitata*)
Phase IV Trap	Dry trap with sticky insert	Ammonium acetate (AA), Putrescine (Pt), Trimethylamine (TMA)	Captures a higher proportion of females, used for detecting wild females in areas with the release of sterile males
Pherocon Trap	Dry trap with adhesive	Ammonium acetate (AA)	For *Rhagoletis* species
Champ Trap	Dry trap with sticky insert	Ammonium bicarbonate (BA)	Specific for *Bactrocera oleae*

Table 2.1: Comparison of different traps used for monitoring Mediterranean fruit fly and other species.

2.2 Smart traps and technological advances

Trap monitoring is an essential element in global pest detection, delimitation, suppression, and eradication programs. For Mediterranean fruit flies, capture devices utilize olfactory and visual stimuli, effectively leveraging specific chemical and visual signals to attract adult flies.

Various types of traps are utilized depending on the specific needs. For instance, McPhail-type traps, which use food attractants, are employed to capture adult fruit flies in non-preventive trapping stages. Conversely, for preventive trapping, Jackson traps and *Phase 4* traps are predominantly used. Most attractants employed in these traps are food-based, releasing ammonia to simulate protein sources [51].

However, the maintenance costs of these traps are considerably high due to the monetary, human, and material resources required to sustain a network of traps. For example, the California Department of Food and Agriculture (CDFA) operates networks comprising approximately 63,000 traps, 30,000 of which are dedicated to detecting Ceratitis capitata (*moscamed*) [14]. These maintenance and manual inspection costs not only limit the spread of the traps but also the frequency with which they can be checked [14]. Consequently, there is a delay in the flow of information since personnel typically visit the traps only once a week [11]. Additionally, there is significant time required to analyze the captured species, as information regarding species and pest densities is primarily acquired through visual inspection [40]. In this process, workers compare the shape, color, texture, and other characteristics of pests [60].

Monitoring population evolution within specific time intervals is nearly impossible due to the relatively low sampling rate [11]. To enhance pest and pathogen control efforts, it is essential to understand the behavior of complex agroecosystems. Modeling an agroecosystem necessitates the analysis of interactive sensing data with high temporal and spatial resolutions [29]. Without a proper understanding of climate-pest interactions, crop producers may experience more harm than benefit, as the cost of pest damage could exceed the cost of control measures [29].

Efficient trap monitoring plays a vital role in controlling the *medfly* across regions. There is a pressing need for more effective monitoring systems for *moscamed* [14]. Developing an autonomous early warning system to detect the presence or resurgence of pests is crucial to reduce the probability of Mediterranean fruit fly spread and establishment [29]. The advancement of such technologies could significantly improve the efficiency of pest control programs, ensuring timely and accurate responses to pest threats. This would involve integrating modern sensing technologies, data analysis, and automated reporting systems to provide real-time updates and actionable insights to pest control personnel. Such innovations are essential for maintaining the delicate balance of agroecosystems and safeguarding agricultural productivity.

The implementation of advanced monitoring techniques and the development of autonomous systems for early pest detection are imperative for the sustainable management of agricultural pests. By enhancing the accuracy and efficiency of pest monitoring, we can better protect crops, reduce economic losses, and minimize the environmental impact of pest control measures.

Automatic monitoring traps, known as *smart traps*, are highly efficient as they can autonomously identify and count pests as they enter the trap [60]. Traditionally, this activity is inefficient due to the manual counting process and the need for technical personnel to travel long distances to access scattered traps in remote areas.

Smart trap devices primarily employ two approaches: (a) capturing images of the trapped insects and (b) detecting insects entering through a tunnel equipped with sensors [14]. Image-based traps capture the surface containing the insects and send these images to a server, where they are processed by recognition software [14]. For effective pest species and density evaluation using artificial vision, a clear image of the insect is crucial. However, capturing clear images is challenging due to the constant movement of the insects [60]. Various implementations of smart traps for capturing the Mediterranean fruit fly are reported in the literature, and Table 2.3 compares these types of traps.

Sensor-based traps typically consist of infrared sensors placed along a tunnel to count the number of times the target insect enters. Unlike imaging systems, these traps do not identify the insect. Therefore, the attractant must be specific to the target pest to avoid erroneous counts caused by non-target species [14]. A comparison of sensor-based traps is shown in Table 2.4.

In the commercial sector, there are three major competitors focusing on fruit fly trapping. Table 2.5 provides a comparison of these commercial smart traps.

The advantage of smart traps lies in their ability to continuously monitor pest populations without the need for frequent human intervention. This reduces labor costs and allows for more timely and accurate pest management decisions. The automated nature of these traps ensures that data collection is consistent and reliable, providing valuable insights into pest behavior and population dynamics.

The integration of smart traps into pest management programs can significantly enhance the effectiveness of these programs. By providing real-time data on pest populations, smart traps enable early detection and rapid response to pest outbreaks. This proactive approach can prevent the spread of pests and reduce the reliance on chemical pesticides, promoting more sustainable agricultural practices.

Moreover, the data collected by smart traps can be integrated into broader pest management systems, allowing for comprehensive monitoring and analysis. This can lead to the development of predictive models that help anticipate pest outbreaks and optimize control strategies. The use of machine learning algorithms and advanced data analytics can further enhance the accuracy and efficiency of these systems.

The adoption of smart traps represents a significant advancement in pest management technology. By automating the monitoring process and providing real-time data, smart traps offer a more efficient, accurate, and sustainable solution for managing pest populations. As technology continues to evolve, it is likely that smart traps will become an increasingly important tool in the fight against agricultural pests. The ongoing development and refinement of these technologies will be crucial in addressing the challenges posed by pest infestations and ensuring the sustainability of agricultural production.

In the commercial field, competition drives innovation, leading to the continuous improvement of smart trap designs. This competitive environment benefits the agricultural sector by providing more effective and user-friendly solutions for pest management. As illustrated in Table 2.5, the advancements in smart trap technology reflect the industry's commitment to enhancing pest control measures and supporting farmers in their efforts to protect crops from harmful pests.

Table 2.2 summarizes the comparison of smart traps for the Mediterranean fruit fly.

Trap Type	**Image-Based**	**Sensor-Based**	**Commercial Competitors**
Efficiency	High	Moderate	Varies
Identification Accuracy	High	Low	Varies
Cost	High	Moderate	Varies
Maintenance	Moderate	Low	Varies
Deployment	Complex	Simple	Varies

Table 2.2: Comparison of Smart Traps for Mediterranean Fruit Fly

Species	**Hardware Used**	**Detection Technique**	**Accuracy Percentage**	**Reference**
Bactrocera dorsalis	2MP camera, microcontroller (MSP430F5436A), SD memory, and GSM/GPRS module (Telit GM862).	Gaussian blur filters and OTSU algorithm for counting.	98–100%	[29]
Dacus ciliatus, *Rhagoletis cerasi*, *Bactrocera oleae*	Modified trap with a camera.	Remote visual inspection.	88%	[51]
-	Camera and GSM modem. No further details reported.	Various pre-trained R-CNN models.	91.5%	[24]

Table 2.3: Comparative table of camera-based traps.

Species	**Hardware Used**	**Detection Technique**	**Accuracy Percentage**	**Reference**
Bactrocera dorsalis	Sensors for measuring wind speed, infrared sensor, temperature and humidity sensors, microcontroller (TI MSP430F449), GPS receiver, and a GSM module.	Remote monitoring	72-92%	[23]

Species	**Hardware Used**	**Detection Technique**	**Accuracy Percentage**	**Reference**
Bactrocera dorsalis	GSM and ZigBee modules. Wireless monitoring is performed at the nodes, and the information is reported to a gateway that eventually transmits the data in a text message. The data is received by a Host Control Platform, where humidity, light, temperature, and the number of captured flies are processed.	Cloud data processing	98–100%	[29]
Bactrocera oleae, *Ceratitis capitata*, *Bactrocera dorsalis*	An infrared sensor is used to measure wingbeat frequency. In another study, the author suggests using Fresnel lenses and stereo recording for the same purpose.	SVM, convolutional neural networks, and other techniques for signal classification.	81-99%	[43], [44]
-	Raspberry Pi, infrared sensor, and Wi-Fi connection.	Flies pass through a tunnel with a sensor at the end that counts the number of elements falling to the bottom.	88-100%	[14]

Species	Hardware Used	Detection Technique	Accuracy Percentage	Reference

Table 2.4: Comparative table of sensor-based traps.

Provider	Characteristics	Services
SnapTrap	High-resolution photos combined with sensors and other trap data. Uses the cellular network to share information and is powered by solar cells.	Optimizes pest management, production, and historical trap images.
RapidAIM	Uses attractants and sensor technology for detection.	Detects the presence of flies, identifies points with the highest number of recognized specimens, receives real-time alerts, shows historical trends, and can register fumigation points and GPS locations.
TRAPVIEW	Works in any area covered by the GPRS or 3G network. Attracts with pheromones and takes photos of attracted pests. Trap images are collected and processed. The system is powered by solar cells.	Automated pest marking and counting, statistical data collection on pests, area-wide pest monitoring, and pest forecasting.

Table 2.5: Comparative table of commercial traps.

2.3 Sensors and detection mechanisms

Several works are reported, and different technologies are applied to monitor and capture Mediterranean fruit fly. For instance, using an optoelectronic sensor to detect wingbeat, Potamitis et al. [43] modified a McPhail trap to monitor its entrance. The goal was to analyze the generated optoacoustic spectrum. The authors detected the fly with an accuracy of 91%. With a modification to the same system, using a bimodal optoelectronic sensor and stereo recording, Potamitis showed in [44] that it is possible to distinguish between fruit fly species (*Ceratitis capitata* and *Bactrocera oleae*) with an accuracy of 98.99%. Different works have been reported with camera sensors because image capture is more robust and can be used for entomologists or image processing systems for decision-making.

For Doitsidis et al. [11], developed a system based on a McPhail trap modified with a camera to monitor *Bactrocera oleae*. The system allowed access to the images remotely, reducing the time spent visiting and collecting data. This system does not add automatic image recognition; only expert entomologists analyze the images. In the same way, Shaked et al. [51] created two systems, one to monitor *Ceratitis capitata* and the other for *Bactrocera oleae*, *Dacus ciliates*, and *Rhagoletis cerasi*. Both were based on a real-time surface image sent to a remote server for image analysis, reaching 88% of accuracy. Kalamatianos et al. [24]; based on a McPhail-type trap, it was equipped with different instruments such as wind and temperature sensors, WiFi, GSM modem, among others. With this system, the authors were able gather data from the field and public a toolkit pre-trained for the identification of the species *Bactrocera Oleae*. In this work proposes an automatic classification of the species using different types of networks convolutional neural networks (CNN) reaching an accuracy percentage of 91.5%. Jiang et al. [23], implement a *smart trap* system based in sensors that operated remotely. The system used a McPhail type trap integrating a microcontroller (MSP430F449) which was responsible for processing GPS information, temperature, humidity, wind speed, and GSM module as interface to connect to a *Host Control Platform* (HCP) to receive commands. The capture module is based on a double infrared sensor placed in line to validate that the fly enters the trap. In addition to the above, the design of the tunnel through which the flies cross; has the measurements just enough to let in only Mediterranean flies. On the HCP side, the information is received and processed to be stored in a SQL table using LabView©. Also using a trap uses a McPhail trap [29], Liao et al. propose an improved mechanism that prevents double counting depending on the route that flies follow. In addition to this, the system implements *nodes* equipped with ZigBee modules to cover larger and more difficult to access areas where the GSM network does not cover. The information from the nodes is transmitted to a *gateway*; which is responsible for sending data to the HCP. Continuing with McPhail traps, Potamitis et al [43] proposed an array of infrared sensors to measure wing beat. The captured signal passes through an analog-digital converter (ADC) which delivers a signal in time and amplitude to which a fast Fourier transform (FFT) is applied to characterize the spectrum in frequency. With this, it was possible not only to identify the Mediterranean fly but also different species. Similarly, the same author proposes in [44], the use of Fresnel lenses. For this case, the light from the infrared LED passes through the Fresnel lens and is collimated. The insect's wings beat cast a shadow on the opposite receiving Fresnel lens. The collimated light is partially dispersed laterally at 90°and directed to the passive Fresnel lens that records the reflected light. Finally, a dark cone-shaped plastic fixes the LED and photodiodes to their correct focal point. Sandrini et al. [50] also propose the use of infrared sensors to measure wing beat, however the signal amplifier output of the sensor is connected to the line input of a sound card. This signal was recorded using Audacity©software and the amplitude of the signals is normalized. An analysis in time and frequency is used to determine the main components and characterize the species.

A novel approach for Mediterranean fruit fly detection is reported by Haff [16] using hyperspectral images. In this work, the authors classified the spots of the fruit fly in mangoes using a hyperspectral camera. The photos were analyzed using Gaussian blur radius, ball radius, and minimum particle size techniques. However, the main problem with this approach is the cost and size of hyperspectral cameras, so this is not a practical solution for the field. In their most recent work, Diller et al. [8] created a surveillance system based on a McPhail trap modified with a camera and Raspberry Pi Zero for trapping and wireless transmission of images to the cloud. Based on deep learning, the algorithm showed great results, reaching a precision of 93-95% for three targets of the specie. Similarly, Uzun reported in [56] the training of deep learning algorithms to detect and count the *Ceratitis capitata* in the field. The algorithm was trained with 722 images, and 150 for validation. The algorithm detected and counted the specie with an accuracy of 99.5%; however, no hardware was embedded in the trap for capturing images. For the same specie, Hernadez et al. in [19], used a radar system to count the number of fruit flies in in captured in a trap. The radar system was able to detect the fruit flies using *shadow effect* which changes the radar intensity when the Mediterranean fly is inside the trap.

From the review, it can be summarized that different sensors have been used to monitor and detect Mediterranean fly in the field. Table 2.6 summarizes the technologies and systems. The most used are cameras, microphones, and opto-electronics sensors. Especially for fruit fly detection, cameras have a particular interest due to their high accuracy and robustness [51]. However, the research for new sensors in *smart trap* systems applied to fruit flies is still in development, and different problems must be addressed.

Reference	**Technology**	**Target Pest**	**Accuracy/Notes**
[43]	Optoelectronic sensor (wingbeat detection)	Mediterranean fruit fly	91% accuracy
[44]	Bimodal optoelectronic sensor	*Ceratitis capitata*, *Bactrocera oleae*	98.99% accuracy
[11]	Camera-based system	*Bactrocera oleae*	Remote image access, no automatic recognition
[51]	Real-time surface image	*Ceratitis capitata*, *Bactrocera oleae*, *Dacus ciliatus*, *Rhagoletis cerasi*	88% accuracy
[24]	McPhail trap with various sensors (WiFi, GSM, etc.)	*Bactrocera oleae*	91.5% accuracy (CNN)
[23]	Smart trap with multiple sensors (GPS, temperature, etc.)	Mediterranean fruit fly	Uses double infrared sensor and micro-controller
[29]	McPhail trap with improved mechanism	Mediterranean fruit fly	Prevents double counting, uses ZigBee modules
[43]	Array of infrared sensors (wingbeat measurement)	Mediterranean fruit fly	FFT applied for species identification
[44]	Fresnel lenses with infrared LED	Mediterranean fruit fly	Collimated light and shadow detection

Reference	Technology	Target Pest	Accuracy/Notes
[50]	Infrared sensors with sound card analysis	Various species	Signal analysis using Audacity©
[16]	Hyperspectral images	Mediterranean fruit fly	High cost and size limitations
[8]	Camera with Raspberry Pi Zero	Mediterranean fruit fly	93-95% precision with deep learning
[56]	Deep learning algorithm (image-based)	*Ceratitis capitata*	99.5% accuracy
[19]	Radar system (shadow effect)	Mediterranean fruit fly	Detects flies inside the trap

Table 2.6: Summary of technologies and systems for monitoring and capturing Mediterranean fruit fly

2.4 Radar technology in entomology

The radar operation is relatively simple: a radio wave is transmitted by an antenna, and some waves are scattered by the object of interest (echo). They are captured back by the same antenna (or another antenna, depending on the radar type) to be processed [47]. The information about the target can be inferred from the difference between the signal that is transmitted-received. The information it provides depends on the design of the radar; however, this can often include distance, direction, speed, and even the target size [18]. The radar allows the detection of these variables using *remote sensing*, that is, applying techniques that acquire measurements from an object using an instrument far from the target [46]. For the radar, the information is present in the intensity, frequency, phase, and modulation of the radio signal; however, the main problem is their interpretation. It isn't easy because it is necessary to determine how the properties of the object (for example, its temperature) are translated by the characteristics of the receiver (for example, the wavelength of the object's light) [13].

In a general classification, there are two types of radars, coherent and non-coherent [34]. Non-coherent radars are characterized by not preserving the phase information contained in the return signal; therefore, the detection is carried out

Letter Designation	Frequency Range in GHz (IEEE Standard)
HF	0.003 - 0.03
VHF	0.03 - 0.3
UHF	0.3 - 1.0
L-band	1.0 - 2.0
S-band	2.0 - 4.0
C-band	4.0 - 8.0
X-band	8.0 - 12.5
Ku-band	12.5 - 18.0
K-band	18.0 - 26.5
Ka-band	26.5 - 40.0
V & W or Millimeter Wave (MMW)	Normally >34.0

Table 2.7: Radar letter classification.

fundamentally based on the amplitude. Non-coherent receivers are often found in simple radar systems since they do not require complicated hardware and software. Coherent radars have a known amplitude and phase for signal processing, such as pulse compression, Doppler processing, mono-pulse comparison, moving target indication, synthetic aperture radar imaging, and adaptive processing space-time [18]. These types of radars are more complex but also allow for obtaining more information about the target.

According to the operation frequency, radars are denoted with a letter set because radars were historically developed for military use. The IEEE (Institute of Electrical and Electronics Engineers) has adopted as a letter set the band. Table 2.7 shows the spectrum associated with each letter set. UHF band is used for very long early warning systems (EWR) for detecting and tracking satellites or ballistic missiles. The primary applications for L-band and S-band radars are ground-based and ship-based systems. The C-band is used for military surveillance, missile control, and ground surveillance. The X-band has applications in missile guidance and airborne imaging. Ka-band is applied to avoid vehicle collisions, police traffic radar, and security monitor detectors. Both radars in V and W-bands suffer from atmospheric attenuation, so their use is limited to short range, with primary applications in the automotive industry for parking assistance or blind spot detection. Radar systems above this band are considered in *Tera Hertz* frequency and are an emerging technology [34].

Radar is the most popular technique among remote sensing solutions [46] because the information is present in the radar signal's intensity, frequency, phase,

	Sensibility			
Sensor	Temperature	Color	Light	Sound/Noise
Infrared	Yes	Yes	Yes	No
Ultrasonic	Yes	No	No	Yes
Radar	No	No	No	No

Table 2.8: Comparison of remote sensing technologies.

and modulation [18]. Compared to other remote sensing techniques, such as infrared or ultrasound, radar is, most of the time, not sensitive to light, color, sound, acoustic noise, or temperature, as shown in Table 5.1.

The radar also has been applied to insect study since the 60s, and this application is known as *radar entomology*. Conventional entomological radars are non-coherent, and the signal amplitude and polarization information received from the insects are used to detect aerial insects' density and class [31]. This type of radar operates at a wavelength of 3.2 cm in the X-band and uses a parabolic antenna with a beam width of one to two degrees. Coherent radars offer better measurement accuracy [3]. With this type of radar, both amplitude and phase information can be used to extract the micro-Doppler frequency induced by the vibratory components of the target. Coherent radars operating the W band are the ones that achieve the best performance in measurement precision and also the smallest measurable size of the insect [13].

Particular challenges that emerge when the radar is applied in entomology are primarily associated with issues originating from the backscattered signal. These drawbacks include, among others: intensity decay, absorption (or complete blockage), scattering (additional reflections), refraction (change of direction caused by the shift in medium), and drift (caused by lateral movements of the medium). The measurement context is another variable that produces problems with radars, for example, when insects settle or crawl on vegetation surfaces. However, this problem can be solved with visual methods such as image analysis. Despite all these limitations, radar continues to be one of the most effective tools for observing insect flight because it works in severe weather conditions and round-the-clock [13].

In the case of radar entomology, it can be focused at the individual or group level on aspects such as migration, behavior, target characterization, and surveillance [13]. For these applications, it is customary to use radars of type scanning, vertical looking (VLR), harmonics, or frequency-modulated continuous wave (FMCW) [42].

The signals provided by the radars are used to estimate the parameters of an isolated insect [32]. For example, to calculate the mass of an insect, in [2] the authors proposed in 1989 to use the radar cross-section of the insect (RCS) since it was observed that there was a logarithmic relationship between the mass of the insect and its average RCS [2]. The RCS quantifies the target's backscatter and characterizes how much of the transmitted signal was intercepted by the target; it depends not only on the material's properties but also on the frequency, polarization, orientation, geometry, and angle of incidence of the transmitted wave [26].

Another parameter that can be determined using the radar is the target's orientation, which according to Long [31], can be calculated using the polarization pattern; the power of the received signal reaches its maximum value when the polarization direction is parallel to the axis of the insect's body. This principle has been shown to perform well for *vertical-looking* type radars (VLR). The wing beating is another parameter that can be calculated using radars, such as radars in the W band. The wing beating causes a fluctuation in the amplitude of the radar signal, producing a periodic modulation and, therefore, it can be used to detect and characterize the wing beating [57].

Other application of radar is insect tracking, which is carried out using the *harmonic radar* technique, which consists of attaching a small transponder to the insect and excite it with the radar to re-emit a new signal at a different frequency [5]. This application has been widely used to study the movement of insects in plantations, such as the study of the displacement of the melon flies, *Zeugodacus cucurbitae*, which are major pests and pose invasion risks [37] or *Vespa velutina*, which preys on pollinating insects [33]. For honeybee surveillance, Nawaf et al. [1] used a 5.8 GHz Continuous-Wave radar to monitor free fly activity. Using machine learning techniques, the authors were able to automated classification of the different activities such as leaving, entering, and hovering.

For insect migration and early detection, the *vertical-looking* radar (VLR) is used. For example, Chapman et al. [4], the authors used a VLR for monitoring migrant insects populations. Rotating the polarization of the radar and nutation, Chapman et al. were able to detect different insects in the air at different altitudes. A database of migration flux was created for different species. In a similar work, Wang et al. [59] also used a VLR to detect different insects in the air but focused on ascent and descent behaviors. Without specify the species, the author was able to detect insects with mass less than 10 mg.

A big problem with radars is related to measurement; small insects reflect radiation that can be hardly observable and, therefore, tricky to interpret. This condition is especially true as the dimensions of the insect become around or less than 5 cm [61]. Measurement is affected not only by size but also by the aspect and relative orientation of the target to the antenna, which directly impacts a small RCS magnitude [13]. Another factor affecting the RCS is humidity, a main reflective component. Hajovsky et al. in 1966 [17] reported that the loss of body moisture affects insects' dispersal properties; the humidity decreased considerably after their death.

Searching the recent literature, different studies have been reported for insect measuring with size dimension smaller than 5 cm. Rui et al. [58] used a X band and Ku-/K band radars to detect different types of moths. Using the RCS, the authors were able to classify the mass and body length. For mass estimation, the authors reached twice the precision compared with traditional methods. For body length, the authors were able to measure body length from 6 to 28 mm using a range of frequencies from 4 to 38 GHz. A similar study was conducted by Wang [20], where the use of support vector regression (SVR) was proposed to estimate the mass of different moth species. In the experiment, the authors used a X-band radar and an microwave anechoic chamber where the moth was attached to a polyethylene line suspended. The size for the different species was not reported.

Continuing with body width and length estimation, Li et al. [28] used a X-band polarimetric radar to estimate the body width and length of different insects. The authors took 159 insects from different sizes and split them in three groups. For small insects, the sizes were in the range of 10 to 20 mm, for medium insects, it was 20 to 30 mm, and for large insects, the size ranged between 30 and 47 mm. They propose empirical equations based on the different RCS parameters to estimate the body width and length of the insects.

Riley [48] using an X-band radar and a transmission line to prevent beam scattered, was able to measure tiny insects (less than 1 cm). Another one was conducted by Wang et al. [57], where it was possible to measure different targets of the species *Mythimna separata* of sizes 10-42 mm using FMCW radars in the W and S bands. For free fly insect monitoring, Diyap et al. [10] used a continuous wave radar in W-band to detect two species: mosquitoes (*Culex pipiens*) and bees (*Apis mellifera*). In both cases, due to the dimension of the insects, the authors used *micro-Doppler* effect generated by wing-beat to detect and classify the species. Simulation and experimental results validated the proposed method.

The Table 5.2 shows a summary of the different studies reported in the literature. As it can observed, the different studies are focused on the estimation of the insect size, mass, body width and length, surveillance or tracking. Also the setup required to measure the insect is heavy and not portable. In this sense, the use of anechoic chambers and heavy equipment was reported. The size of the insect is not reported in all the studies, but the smallest insect was 10 mm. Regarding to the species, the most common insects are moths, and bees. The most common radar used is the X-band, Ku-band, and W-band. For the radar type, mainly FMCW, VLR and CW are used.

Reference	**Radar Type**	**Band**	**Application**	**Insect Species**	**Dimensions**
[57]	Coherent	W (93.6 GHz) and S (3.3 GHz)	Wing-beat detection	*Mythimna separata*	10-42 mm
[5]	Harmonic	X (9.4 GHz)	Tracking	*Vespa velutina*	20 mm
[1]	CW	C (5.8 GHz)	Surveillance	Honeybees (species not reported)	Not reported
[59]	VLR	Ku (16.2 GHz)	Detection and tracking	Various insects	Not reported
[58]	Multifrequency	X (8.25–11.75 GHz), Ku (17.75–18 GHz), and K (18–23.75 GHz)	Morphological parameter estimation	Various moth species	6-28 mm
[20]	SFCW	X (9.4 GHz)	Mass estimation	Various moth species	Not reported
[28]	Polarimetric	X (9.4 GHz)	Width and length estimation	Various insect species	10-47 mm

Reference	**Radar Type**	**Band**	**Application**	**Insect Species**	**Dimensions**
[48]	-	X	-	Aphids and planthoppers	Not reported
[10]	CW	W (94.3 GHz)	Wing-beat classification	*Culex pipiens* (mosquitoes) and *Apis mellifera* (bees)	Not reported

Table 2.9: Summary of the different studies reported in the literature on radar-based insect detection.

Chapter 3

Materials and methods

3.1 Design of the smart delta trap

The Smart Delta Trap, meticulously designed using Fusion 360, showcases an innovative approach to insect monitoring and control. This design combines functionality and aesthetics, ensuring efficiency in capturing insects while maintaining a sleek, modern look. The trap is composed of several integral components, each designed to serve a specific purpose. The images provided offer a comprehensive view of the trap from different angles, illustrating its detailed and thoughtful design.

3.1.1 Main Body and Structure

The main body of the trap is a robust, triangular structure designed to provide stability and durability. The desing is based on the delta trap, which is a widely used in field conditions for MoscaMed program. The triangular design is not only structurally sound but also maximizes the surface area for insect attraction. The base of the trap is wide, ensuring that it remains stable when placed in various environments. The sides of the triangular frame are reinforced to withstand outdoor conditions, making the trap suitable for various weather conditions. The Figure 3.1 a) shows the trap body and structure, highlighting the attention to detail in the design of the main frame.

3.1.2 Ventilation and Accessibility

Figure 3.1 d) shows the trap with its lid. The lid is designed to provide structural support to hold the lure securely. The design incorporates ample ventilation to ensure proper airflow through the lure, allowing sensors to receive accurate readings. This ventilation is crucial for sensors like the SGP30, which measure air quality and volatile organic compounds (VOCs). Additionally, the design retains the familiar elements of current traps used in the field, thereby eliminating the need for revalidation of the trap design.

3.1.3 Top Panel and Sensor Integration

The top panel of the trap is designed to house several essential components. As shown in Figure 3.1 c) , the top panel includes multiple cutouts and slots for sensors and electronic components. These cutouts are strategically placed to ensure that the sensors can operate effectively without being obstructed. The integration of sensors like the SGP30 and ENS160, which are visible in the design, allows the trap to monitor environmental conditions and detect the presence of insects through their emissions.

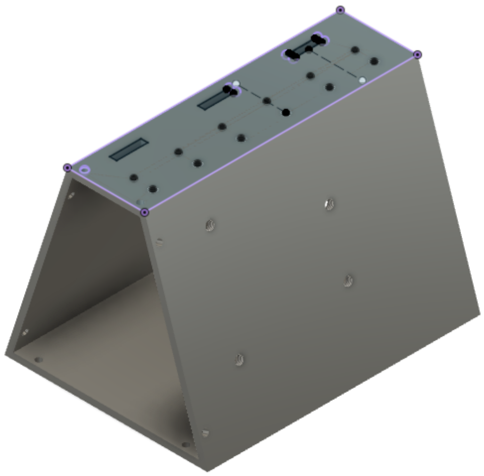
3.1.4 Assembly and Electronics Housing

Figure 3.1 d) highlights the intricate assembly of the trap. The design includes a dedicated compartment for housing the electronic components, ensuring they are protected from external elements. This compartment is designed with precision, featuring ventilation slots to prevent overheating and maintain optimal operating conditions for the electronics. The placement of the electronic housing ensures that the trap's functionality is not compromised while keeping the components accessible for maintenance.

3.1.5 Structural Reinforcements

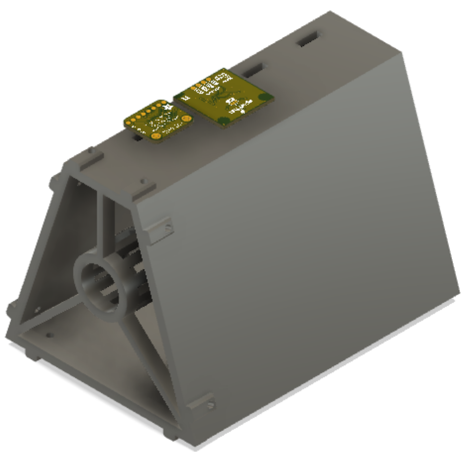
The internal frame is designed to hold the main components securely, ensuring they remain in place during operation. The design includes brackets and supports that add to the trap's overall stability. These reinforcements are crucial for maintaining the structural integrity of the trap, especially when it is subjected to outdoor elements.

The Smart Delta Trap's design in Fusion 360 is a testament to thoughtful engineering and design. By integrating advanced sensors and ensuring robust structural support, the trap offers a reliable solution for monitoring and controlling insect populations. The images illustrate the meticulous attention to detail in every aspect of the design, from the placement of electronic components to the overall structural integrity. This trap not only serves its functional purpose but also represents a sophisticated piece of equipment that can be utilized in various environments for effective insect monitoring and control. It is impotant to note that this was the first version of the trap and the technical specifications and design will be discussed in the next chapter.

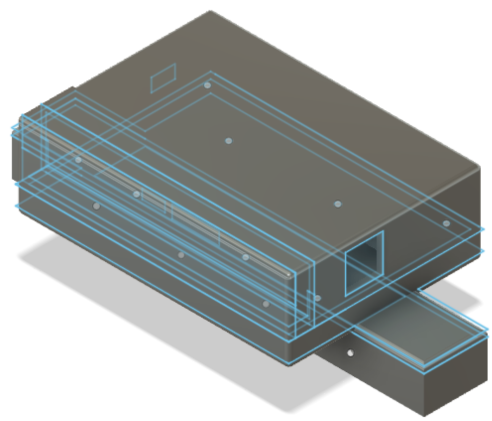


a) Trap body and structure.

b) Trap lid with sensor integration.



c) Trap assembly with electronic components.



d) Trap case to hold main board.

Figure 3.1: Design of the Smart Delta Trap.

3.2 Description of sensors and radar systems used

The Smart Delta Trap is equipped with a variety of sensors and radar systems to monitor Mediterranean fruit fly populations. In the implementation of a comprehensive system for crop pest detection through different sensors and image processing, so the selection and integration of various sensors and radar systems are crucial for ensuring the system's effectiveness and reliability. This section details the specific sensors employed in the project, elucidating their functionalities and the role each plays in ensuring the accuracy and reliability of the detection system.

3.2.1 Camera Sensor

The camera sensor is a pivotal component in this system, primarily responsible for capturing high-resolution images inside the trap. These images serve as the primary data source for image processing algorithms designed to identify and classify different species of insects. The camera sensor must offer high resolution, fast shutter speed, and adaptability to varying lighting conditions to ensure clear and detailed imagery. lthough the images are captured solely in the visible spectrum, this capability allows for the identification of species that might not be easily discernible to the naked eye.

3.2.2 Temperature, Humidity, and Pressure Sensor

Environmental factors such as temperature, humidity, and atmospheric pressure significantly influence pest behavior and population dynamics for Mediterranean fruit flies. Therefore, a sensor capable of measuring these parameters is integrated into the system. The data collected by the temperature, humidity, and pressure sensor helps in understanding the environmental conditions that correlate with pest infestations. This sensor provides real-time environmental data, which is essential for the accurate interpretation of pest presence and activity patterns.

3.2.3 Air Quality Sensors

Air quality sensors play a critical role in monitoring the concentration of volatile organic compounds (VOCs) and other pollutants that may indicate the presence of pests or their metabolic activities. By measuring parameters such as carbon dioxide, ammonia, and other gas concentrations, these sensors can provide infomrmation about the lure presence and its degradation. The integration of air quality sensors enhances the system's avoiding trap visits when the lure is not effective, thereby reducing unnecessary costs and labor.

3.2.4 Color Sensor

The color sensor is employed to detect changes within the trap, thereby informing decisions regarding camera activation. By monitoring variations in color, this sensor can identify the presence of insects or other triggers that necessitate image capture. This proactive approach ensures that the camera is only activated when relevant changes occur, optimizing power consumption and enhancing the efficiency of the system. The color sensor's ability to detect subtle shifts in coloration provides a reliable mechanism for determining the appropriate moments for image acquisition, thereby improving the overall effectiveness of pest detection.

3.2.5 RTC Sensor

The Real-Time Clock (RTC) sensor is essential for timestamping the data collected by other sensors. Accurate timekeeping is crucial for correlating environmental conditions, air quality, and pest detection data. The RTC sensor ensures that all data points are synchronized, enabling a precise analysis of temporal patterns in pest activity and environmental changes. This synchronization is vital for developing predictive models and understanding the cyclical nature of pest infestations.

3.2.6 Radar Sensor

The radar sensor is employed to detect the presence of insects within its range, providing critical data on their movements and activities. This sensor is particularly useful for monitoring nocturnal conditions, where traditional visual methods may fail due to low light levels. Additionally, the radar sensor's ability to operate under various weather conditions—such as rain, fog, or strong sunlight—ensures consistent and reliable performance. Its non-intrusive nature means it does not disturb the insects or the surrounding environment, making it an invaluable component of the pest detection system. By continuously monitoring insect activity, the radar sensor helps in early detection and timely intervention, thereby enhancing the overall effectiveness of pest management strategies.

3.2.7 WiFi

The inclusion of WiFi capabilities facilitates the seamless transmission of data from the sensors to a central processing unit or cloud-based storage. This connectivity allows for real-time monitoring and analysis, enabling prompt responses to pest detections. WiFi also supports remote access to the system, allowing researchers and farmers to monitor crop conditions and pest activities from any location. The integration of WiFi ensures that the data collected is not only readily accessible but also can be analyzed in conjunction with other relevant datasets, enhancing the overall effectiveness of the pest detection system.

The fusion of these diverse sensors and radar systems forms a robust and comprehensive framework for mainly Mediterranean fruit fly detection and monitoring. Each sensor contributes unique and valuable data, which, when integrated, provides a holistic view of the crop environment and pest dynamics. This multidisciplinary approach leverages the strengths of various sensing technologies to achieve accurate and timely pest detection, ultimately contributing to more effective pest management strategies in agricultural settings.

3.3 Trap configuration and experimental setup

Among the sensors described above, the air quality sensors and radar sensor required special attention in the experimental setup. The air quality sensors were used to detect the presence of the lure in the trap, while the radar sensor was employed to detect the presence of the flies. The other sensors did not need special setup and were simply integrated into the trap at positions optimal for measuring the desired parameters.

For the air quality sensors, a modified Delta trap (also known as a Jackson trap) is used. This design is chosen because it is widely used in the field in Mexico and allows for effective integration of sensor hardware. The trap design includes slots at the top for placing air quality sensors, and the traps are constructed using a 3D printer and biodegradable PLA material. The design retains the traditional dimensions of Delta traps but features a central basket to stabilize the lure's position within the trap.

Two types of Metal Oxide (MOX) gas sensors are used: the SGP30 and ENS160 from ScioSense®. These sensors measure the air concentration of Volatile Organic Compounds (VOCs) (TVOC, Total VOC) and equivalent Carbon Dioxide (eCO2). The ENS160 requires a warm-up period of up to 20 minutes and is suitable for high-power applications, while the SGP30 is suitable for low-power, battery-operated devices and reaches stability after three minutes. The sensors are managed by an STM32F401 microcontroller board, featuring a 32-bit ARM Cortex-M4 core, 512 KB of flash memory, and 96 KB of RAM. Communication is facilitated via an I2C interface, programmed using STM32CubeIDE software in C language.

Initial tests are conducted in a controlled environment (a clean room maintained at 25°C and 20% relative humidity) to establish baseline noise levels for the sensors. The lure (Trimedlure©) is placed at varying distances (1 cm, 2 cm, and 3 cm) from the sensors within the trap.

For the radar sensor, the experimental setup initially involve using a polystyrene base for all measurements to avoid variations in the reflectivity graphs. To characterize the radar, metal spheres of sizes 3, 4, 5, 6, and 15 mm are used to measure reflectivity. These metal spheres are placed on the polystyrene base to characterize the radar and determine the detection zone. The 5 mm sphere was specifically used to match the size of Mediterranean fruit flies.

After characterizing the radar, the base is changed to a glue base used in the field to ensure realistic measurements. Flies are added to the glue base after the bottom is characterized. Measurements are taken using two types of lenses: Fresnel Zone Plate (FZP) and Hyperbolic (HBL) lenses, with variations in two parameters: Hardware Acceleration Average Sample (HWAAS) and gain. Measurements are made with gain values of 0.1, 0.2, and 0.3, and HWAAS values of 15, 30, and 40.

The radar used is a pulsed W-band radar (Acconeer©A111) operating at 60.5 GHz with a spatial resolution of 5 mm. Radar configuration includes adjusting antenna gain between 0.0 and 1.0, starting at 0.1 to avoid ADC saturation, initially setting HWAAS to 15 to reduce signal noise, disabling power save mode to ensure optimal performance, setting the update rate to 30 Hz, using the maximum resolution profile for close range (less than 20 cm), and setting the range between 10 and 26 cm. One thousand sweeps are performed to obtain a single measurement, which is then averaged to minimize noise impact.

Chapter 4

Development of the smart delta trap

4.1 Design considerations and challenges

This section outlines the methodology required to develop a *smart trap* system based on the specific objectives and proposed hypothesis.

4.1.1 Requirements

The components necessary for the *smart trap* system vary according to the design but include the following key elements:

- Temporal resolution, defining the monitoring frequency (e.g., daily, weekly).
- Verification data for validating the automatic counting module.
- A Mediterranean fly detection algorithm [14].
- An online interface for accessing and analyzing historical detection data.
- An alert system to notify administrators in case of an outbreak to mitigate economic losses [29].

Additionally, interviews with Ecosur staff identified further requirements:

- Powering the system with batteries or solar cells.
- Automatic insect detection within the trap, with event time recording.

- Remote access to the trap's status via a camera.
- Geographical positioning of the trap.
- Recording the level of attractant available.
- Recording weather conditions.
- A unique identifier number for each trap.
- Deployment of a network of traps.
- Cost-effectiveness compared to existing commercial solutions.

4.1.2 Determine Components

Developing the *smart trap* system involves integrating software, hardware, and mechanical components.

In the domain of hardware development, it is imperative to integrate the requisite instrumentation to fulfill the specifications of various input variables. This integration is critical given that the system in question is passive and, as such, does not employ actuators. The instrumentation must be meticulously selected and integrated to accurately capture and process the necessary input data, ensuring that all system requirements are adequately met.

The absence of actuators implies that the system relies solely on the passive collection and monitoring of data, without the capability to initiate any active mechanical movements or adjustments. Therefore, the hardware components, including sensors and related circuitry, must be optimized for precise and reliable data acquisition. These components should be capable of operating within the specified parameters and environmental conditions, ensuring consistent performance and accuracy.

Furthermore, the instrumentation must be designed to seamlessly interface with the system's control and processing units. This involves ensuring compatibility with the data acquisition protocols and communication interfaces used within the system. The goal is to achieve a harmonious integration where the hardware components effectively gather and relay input data to the processing units for subsequent analysis and utilization.

Software development encompasses multiple layers, each serving distinct but interrelated functions. At the foundational level, low-level firmware is crucial for establishing and maintaining connections with the hardware. This firmware is responsible for controlling hardware components, managing communication protocols, and ensuring seamless integration between the software and the physical devices. It operates close to the hardware, providing essential instructions and managing operations critical to the hardware's functionality.

On the other hand, high-level applications are developed to implement the various required services that the system must deliver. These applications are built on top of the low-level firmware, leveraging the foundational control and connectivity established by the firmware to offer more complex and user-facing functionalities. High-level applications encompass a broad range of software, including user interfaces, data processing algorithms, network communication modules, and other service-oriented components. They are designed to interact with the end-users, providing the necessary tools and interfaces for operating the system, processing data, and delivering the intended services.

Together, these layers form a comprehensive software architecture that ensures efficient hardware utilization and delivers high-level services to users. The low-level firmware acts as the backbone, facilitating direct hardware management and interaction, while the high-level applications provide the sophisticated functionalities and user-centric operations that define the overall system performance and user experience. This layered approach in software development ensures that each component operates efficiently within its domain, contributing to a cohesive and robust system architecture.

Finally, the intention behind the mechanical design in smart trap is to create a functional, reliable, and manufacturable physical structure for the product. It begins with ensuring the structural integrity of the product, making sure it can withstand operational and environmental stresses throughout its lifecycle. This involves selecting appropriate materials and designing a robust structure that guarantees durability and safety.

Different engineering methodologies, known as *design processes*, address these stages. Examples include the V model, waterfall, spiral, incremental, iterative, and *agile* processes. Each methodology adapts to specific development contexts.

For software development, the V model involves stages such as requirements analysis, system design, architecture design, module design, coding, unit testing, integration, and system testing. For hardware, it includes requirements, schematic design, PCB manufacturing, hardware testing, system testing, and production. This highlights the distinct processes for each component.

This document will follow the *V model* methodology, as it provides the necessary stages from requirements to testing. Additionally, it allows for client interactions to refine or correct development, making it somewhat iterative.

4.2 Sensor integration and hardware implementation

Based on the requirements, the analysis for determining the necessary components will be divided into hardware, software, and mechanical systems.

4.2.1 Hardware components

This section outlines the hardware design process. As shown in Figure 4.1, the first stage in hardware design is defining requirements, which has been covered previously. The next stage is schematic design, requiring component selection for the schematic.

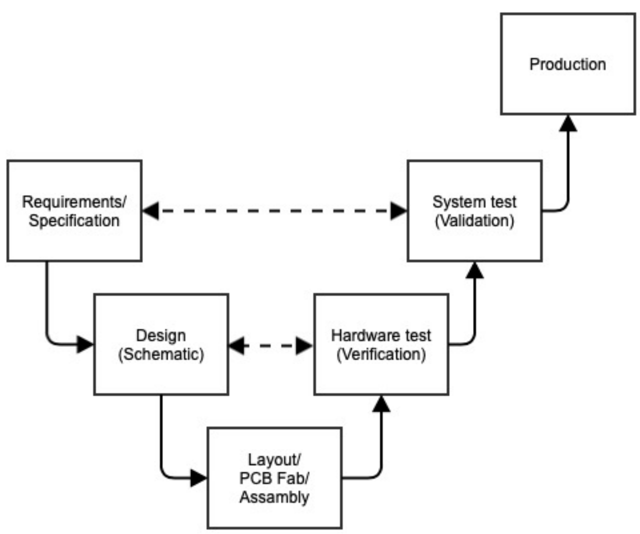


Figure 4.1: Hardware design process.

To implement the proposed hypothesis, it is essential to acquire data from two primary sources: a camera and a radar system. In addition, the system necessitates an independent power supply, which can be provided by batteries or solar cells, to ensure uninterrupted operation. The integration of sensors to measure temperature, humidity, pressure, attractant level, and internet connectivity is also required. These sensors must provide precise and reliable data to support the system's functionality.

Given these stringent requirements, relying solely on a microcontroller (MCU) is inadequate, particularly for the demanding task of image processing. A more suitable solution is the deployment of a system on chip (SoC). An SoC integrates various high-level components within a single chip, each capable of managing complex tasks. These components typically include central processing units (CPUs), digital signal processors (DSPs), various peripherals, and microcontroller units (MCUs). The integration of these elements into a single chip allows for a highly efficient and capable system, providing the computational power needed for advanced tasks such as image processing while maintaining low power consumption.

The SoC architecture offers several advantages, making it ideal for the core of the trap development. Its ability to consolidate multiple processing units and peripherals into one compact and efficient package reduces the overall system complexity and enhances performance. The low power consumption of SoCs is particularly beneficial in applications requiring extended operation on battery or solar power. Additionally, the integrated nature of SoCs simplifies the design and implementation process, leading to more reliable and maintainable systems.

SoC technology offers several options depending on the application. For rapid prototype development and easy integration of new components, Octavo Systems provides not only SoC technology but also system in package (SiP) technology. SiP technology integrates multiple integrated circuits (ICs) and passive components into a single package, as shown in Figure 4.2. This approach leverages semiconductor manufacturing processes and bare silicon die to create a closely coupled module. SiP technology facilitates the design process by providing subsystems that can be directly connected, eliminating the need for extensive routing and allowing focus on value-adding features. Additionally, SiP technology enables rapid validation by focusing on system integration, saving engineering effort and reducing the likelihood of design errors.

Among the chips offered by Octavo Systems, the OSD32MP15x best fits the requirements. It features a heterogeneous architecture with two Arm®Cortex®A7 cores and one Arm®Cortex®M4 core, supporting both hard and soft real-time applications.

Following the selection of the processor, the subsequent phase involves the selection of appropriate sensors. In the context of the camera, available information regarding resolution is somewhat limited. Notably, [29] references a 2

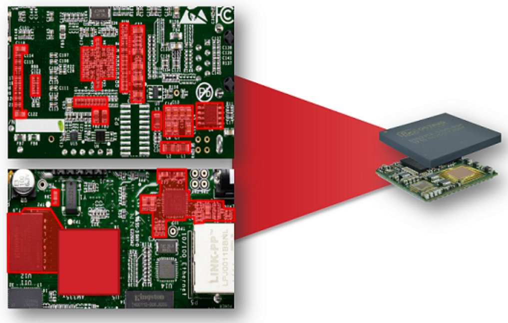


Figure 4.2: Example of SiP technology. The parts marked in red are integrated into the chip, reducing design size, expense, and speeding up development.

Megapixel resolution, yet does not specify the interface utilized for connection. The OSD32MP15x processor, however, provides support for both DCMI and USB interfaces for camera management.

Given the necessity for flexibility in adjusting resolution parameters, the USB interface emerges as the most advantageous option for the initial prototype. This choice facilitates straightforward modifications to resolution settings without necessitating changes to the hardware, interface, or software, thereby streamlining the development process.

For the initial prototype, the LI-OV5640-USB-AF 5 Megapixel camera from Leopard Imaging has been selected. This camera's USB interface aligns with the processor's capabilities, ensuring compatibility and ease of integration. Furthermore, the higher resolution offered by this camera model provides a greater degree of detail and accuracy in image capture, which is essential for the system's functionality.

This careful selection of the camera, considering both resolution and interface compatibility, ensures that the prototype will meet the required specifications while allowing for future adjustments and enhancements with minimal disruption to the overall system design. This strategic approach not only facilitates the current development phase but also provides a robust foundation for subsequent iterations and improvements.

For the selection of the radar sensor, it is imperative to consider several critical criteria: detection range and low power consumption. The detection range must be precise, operating on the order of millimeters, to accurately detect the Mediterranean fly, which measures between 3 to 5 millimeters in size. Additionally, due to the constraints imposed by the system's limited power source, the radar sensor must exhibit minimal power consumption. This is particularly crucial as the system requires continuous presence detection to identify when a species enters the trap.

Among the available options, the Acconeer A111 radar sensor stands out as the optimal solution. It uniquely guarantees measurements within the millimeter range, which is essential for detecting the small dimensions of the Mediterranean fly. Furthermore, the Acconeer A111 offers advanced signal processing capabilities, providing separate management of the received signal in terms of amplitude, phase, and time. This level of detailed signal management enhances the accuracy and reliability of the detection system, ensuring precise identification of the target species.

The Acconeer A111's combination of precise measurement capabilities and low power consumption makes it ideally suited for integration into the trap system. Its ability to operate effectively within the specified parameters ensures that the radar sensor will perform reliably under the constraints of continuous operation and limited power availability. This careful selection underscores the importance of aligning sensor capabilities with system requirements to achieve optimal performance in the intended application.

To effectively monitor the attractant level within the trap, it is imperative to integrate sensors that measure temperature, humidity, and pressure. These environmental parameters are crucial for assessing the efficacy and condition of the attractant. Typically, these sensors are consolidated into a single chip, streamlining the design and implementation process. The primary considerations for selecting these sensors include the connection interface—commonly SPI or I2C—and the precision of the measurements.

The MS8607 sensor emerges as an exemplary choice for this application. It offers a combination of ultra-low power consumption, high precision, and compact size, making it well-suited for the trap system's operational requirements. The ultra-low power consumption is particularly advantageous, given the system's dependence on a limited power source, such as batteries or solar cells. High precision in measuring temperature, humidity, and pressure ensures that the environmental conditions affecting the attractant are accurately monitored, thus maintaining the trap's effectiveness.

Furthermore, the compact size of the MS8607 facilitates its integration into the trap's design, allowing for a more streamlined and unobtrusive sensor deployment.

This integration enhances the overall functionality of the trap without imposing significant additional space or power requirements. By leveraging the advanced capabilities of the MS8607, the trap system can achieve reliable and precise environmental monitoring, thereby optimizing the performance and longevity of the attractant and, consequently, the efficacy of the trap itself.

To effectively sense the attractant level within the trap, it is essential to identify the specific chemical components emitted. In the case of trimedlure, these components predominantly include ketones and aldehydes. These volatile organic compounds (VOCs) are readily detectable using gas sensors designed for air quality measurement.

For this purpose, the SGP30 and ENS160 sensors have been selected. Both sensors incorporate a metal-oxide gas (MOX) sensing element, which is particularly effective for detecting a broad range of VOCs, including ketones and aldehydes. These sensors are equipped with an integrated microcontroller unit (MCU), an analog-to-digital converter (ADC), and an I2C interface, facilitating seamless communication with the system's processing unit.

Moreover, the SGP30 and ENS160 sensors are designed for low power consumption, which is a critical attribute given the system's reliance on a limited power supply. This low power requirement ensures that the sensors can operate continuously without imposing significant additional load on the power source. The inclusion of an MCU within the sensors enables pre-processing of the sensor data, thereby reducing the computational burden on the main processing unit and enhancing overall system efficiency.

The integrated ADC within these sensors converts the analog signals from the MOX sensing element into digital data, which can be easily processed by the system. The I2C interface allows for straightforward integration with the system's existing communication infrastructure, enabling quick and efficient data transfer without necessitating additional hardware or software modifications.

The selection of the SGP30 and ENS160 sensors for detecting the attractant level in the trap system is informed by their ability to accurately sense VOCs, their low power consumption, and their ease of integration. These attributes collectively ensure that the sensors can be incorporated into the system with minimal effort while providing reliable and precise measurements of the attractant's chemical components. This enhances the overall functionality and effectiveness of the trap system in monitoring and maintaining optimal attractant levels.

Finally, the integration of a color sensor is employed to monitor the ambient light levels within the trap. This strategy is intended to minimize the frequency of camera activations, thereby conserving power. In addition to its role in power management, the color sensor supplies valuable data regarding the lighting conditions inside the trap, which can be leveraged to enhance the performance of the detection algorithm.

For this application, the AS73211 sensor has been selected. This sensor is renowned for its precise color sensing capabilities, making it highly suitable for the intended purpose. The AS73211 is capable of providing detailed information on the light spectrum, including intensity and color composition. Such comprehensive data allows the system to determine the optimal conditions for activating the camera, ensuring that power is only utilized when necessary.

Furthermore, the accurate color sensing provided by the AS73211 sensor can significantly improve the efficacy of the detection algorithm. By analyzing the light conditions, the algorithm can be fine-tuned to distinguish between different states of trap occupancy more effectively. This enhancement in detection capability is crucial for maintaining the reliability and accuracy of the system.

The AS73211 sensor's integration into the trap system is facilitated by its advanced features and compatibility with standard communication protocols. Its low power consumption and high precision make it an ideal component for applications where power efficiency and accuracy are paramount.

The deployment of the AS73211 color sensor within the trap system serves a dual purpose: it reduces unnecessary camera activations, thereby conserving power, and it provides critical data on ambient light conditions, which can be used to refine the detection algorithm. This integration ensures that the trap system operates efficiently and effectively, with optimized power usage and enhanced detection capabilities.

At this stage, significant progress has been made in identifying several essential components required for the system's implementation. However, additional components, particularly those related to power management, remain to be selected and integrated. Figure 4.3 presents a block diagram illustrating the first prototype of the system.

The subsequent step in the design process involves the integration of the identified components into a comprehensive schematic diagram. This phase is crucial, as it necessitates the validation of the proposed design's operational efficacy. To ensure the prototype and proposed design function as intended, rigorous evaluation will be conducted using the OSD32MP1-RED evaluation board.

This evaluation board provides a robust platform for testing and validating the system's components and their interactions. It allows for thorough examination and debugging, ensuring that each component operates correctly within the overall system architecture. The insights gained from this evaluation will inform any necessary adjustments or optimizations, thereby enhancing the reliability and performance of the final design.

A notable advancements have been achieved in defining the system's components, further sections will describe the integration of these components into the system and what are the efforts required to incorporate additional elements, particularly in power management.

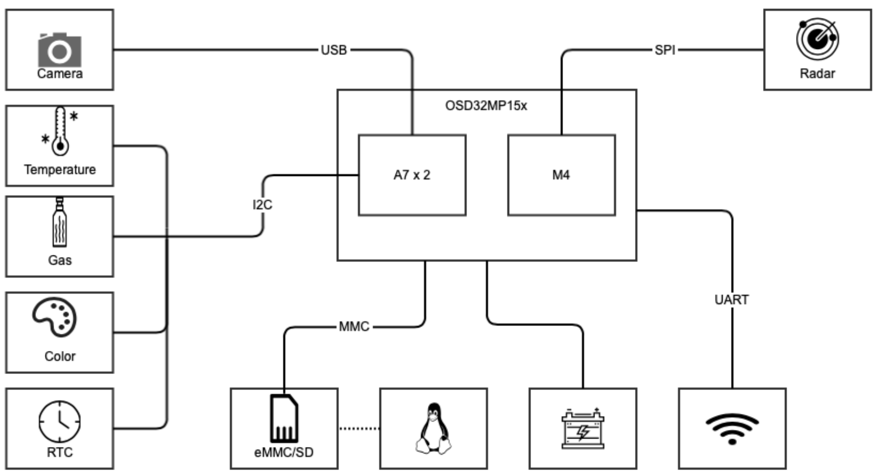


Figure 4.3: Block diagram of the hardware to be developed.

4.3 Software development for data analysis

Following a methodology analogous to that employed in the hardware design process, the software design process is depicted in Figure 4.4. This section concentrates on the system and architecture design stages, given that the requirements have already been delineated.

In the initial stages of software design, it is imperative to establish a comprehensive understanding of the system architecture. This involves defining the overall structure and organization of the software components, ensuring that they align with the specified requirements. The architecture design phase serves as a blueprint, guiding the development process and ensuring that all components integrate seamlessly.

The system design phase focuses on the high-level structure of the software, outlining the key modules and their interactions. This includes specifying the functional and non-functional requirements, identifying the primary components, and defining the interfaces between them. The objective is to create a cohesive and scalable architecture that can accommodate future modifications and enhancements with minimal disruption.

During the architecture design stage, various architectural patterns and frameworks are evaluated to determine the most suitable approach for the system. This includes considering factors such as performance, scalability, maintainability, and security. The chosen architecture must provide a robust foundation that supports the efficient development and deployment of the software.

Furthermore, detailed design specifications are developed for each component, outlining their responsibilities, data structures, and algorithms. These specifications serve as a reference for developers, ensuring consistency and adherence to the overall architectural vision.

By adhering to a systematic and methodical approach, the software design process aims to create a well-structured and efficient system that meets the defined requirements. The subsequent phases of development, including implementation, testing, and deployment, are guided by the architectural design, ensuring a coherent and effective software solution.

The software design process, as illustrated in Figure 4.4, focuses on the critical stages of system and architecture design. This structured approach ensures that the software components are well-defined, integrated, and aligned with the specified requirements, providing a solid foundation for subsequent development activities.

System design entails representing the components of a system from a broad perspective using graphical notations, such as Unified Modeling Language (UML). This stage purposefully omits intricate details to enhance clarity and facilitate understanding among stakeholders. Various models are developed to depict the system from multiple viewpoints, aligning with the methodology suggested by [53].

Initially, a structural view of the system is provided, serving as a foundational representation that outlines the primary components and their interrelations. This approach allows for a comprehensive understanding of the system's architecture

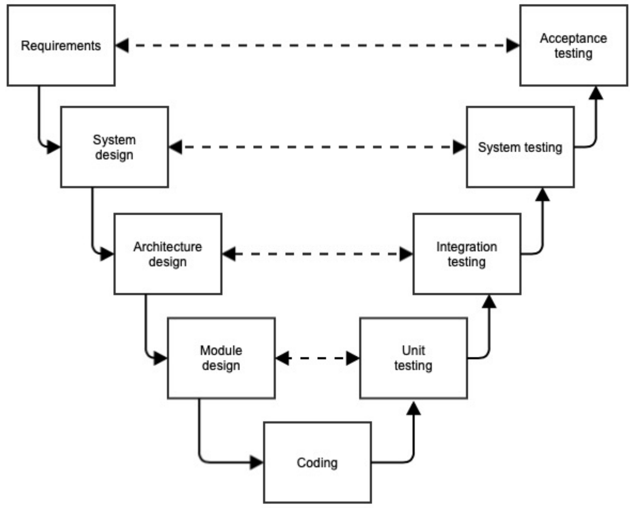


Figure 4.4: Software design process.

without delving into the complexities that might obscure the overall vision.

The accompanying diagram (Figure 4.4) illustrates the software design process, mirroring the methodology employed in hardware design. This visual representation underscores the systematic progression from requirements to acceptance testing, highlighting the iterative nature of system design and validation.

As depicted in the diagram, the system design phase is followed by architecture design, which further refines the structural view into more detailed components and their interactions. This stage is critical for identifying the high-level architecture that will guide subsequent development phases.

Module design comes next, focusing on the detailed specification of individual components. This is followed by coding, where the actual implementation of the design takes place. Unit testing ensures that each module functions correctly in isolation, while integration testing verifies the interaction between modules.

System testing encompasses the evaluation of the complete system to ensure it meets the specified requirements. Finally, acceptance testing involves validating the system against user needs and expectations, marking the culmination of the design and development process.

By adhering to this structured approach, system design ensures a coherent and comprehensive architecture that aligns with both functional and non-functional requirements. This methodical process not only facilitates understanding but also enhances the reliability and maintainability of the final system.

4.3.1 System Design for the SoC

For the OSD32MP15x SoC, which supports a Linux operating system (Figure 4.3), an embedded Linux system comprises four essential components [52]:

- *Toolchain*: This includes the compiler and other tools necessary for creating code tailored for the device.
- *Bootloader*: This program initializes the SoC and subsequently loads the Linux kernel.
- *Kernel*: Responsible for managing system resources and interfacing with the hardware.
- *Root file system (rootfs)*: Contains the libraries and programs executed after the kernel completes its initialization.

Manually configuring and compiling each component is unnecessary; instead, a build system can be utilized. The two most prominent build systems are Yocto and Buildroot. These systems automatically search for and compile the required components, creating a complete image ready for deployment. The SoC supports a Yocto-based system called OpenSTLinux, which provides extensive configuration options and several key components [55]:

- *OE-Core*: Manages core metadata.
- *OpenEmbedded BitBake*: A task scheduler responsible for compiling the necessary components to create the distribution.
- *Poky*: The reference distribution.
- *Documentation*: User manuals and developer guides for each component.
- *Toaster*: A web-based interface to BitBake and its metadata.

The Yocto Project provides a stable foundation that can be used as is or extended with additional *layers*. The first layer, typically provided by SoC vendors, is the board support package (BSP), which primarily contains recipes for the bootloader and kernel. Additional layers can be added to create extended or customized build systems.

In summary, the Yocto build system operates as follows: BitBake parses files known as *recipes* and schedules tasks for the compiler. Recipes can inherit from other recipes, override or add tasks, and customize variables, allowing for extensive customization. This approach saves time and accelerates development, enabling a focus on the *root file system* and application.

Figure 4.5 summarizes the layered architecture provided by OpenSTLinux (Yocto) for the SoC.

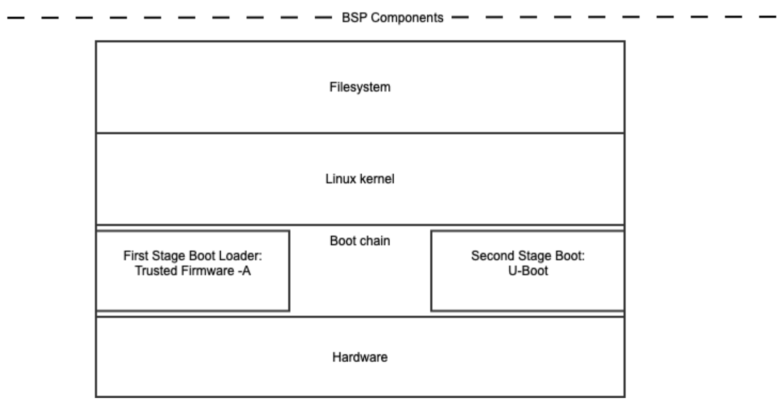


Figure 4.5: Layered architecture for OpenSTLinux.

4.3.2 Architecture Design for the Application

The architecture design phase is pivotal in the development process as it focuses on establishing the overall structure of the system and systematically organizing its components. This phase serves as a critical juncture, bridging the gap between the conceptual design and the specific requirements of the system. It involves identifying the key structural components and elucidating their interrelationships, resulting in a comprehensive model that delineates the system's organization and communication pathways.

According to [53], inadequate architectural design can severely impair a system's performance, robustness, distributability, and maintainability. Consequently, this stage is of paramount importance because any subsequent changes or refactoring can be exceedingly costly, necessitating modifications across numerous system components.

To mitigate such risks, it is imperative to meticulously identify the primary components that embody high-level characteristics, ensuring that functions or features are appropriately grouped within specific components or subsystems. The architectural design process can be conducted at two distinct levels of abstraction:

- *High-Level Design (HLD)*: This level focuses on the broader system architecture, outlining the major components and their interactions. It provides a macro perspective, highlighting the system's overall structure without delving into the intricate details. High-Level Design is essential for understanding how different parts of the system collaborate to achieve the desired functionality and performance.

- *Low-Level Design (LLD)*: This level delves into the finer details of the system architecture, specifying the internal workings of each component. It includes detailed diagrams, data structures, algorithms, and interface definitions that guide the implementation phase. Low-Level Design ensures that each component is designed to meet the specified requirements and integrates seamlessly with other components.

The architecture design phase culminates in a model that not only maps out the system's structural framework but also delineates the communication pathways between components. This model serves as a blueprint for subsequent development activities, guiding the implementation, testing, and maintenance phases. By adopting a methodical approach to architecture design, developers can create a robust, scalable, and maintainable system that meets the specified requirements and performs efficiently in its operational environment.

Developing a detailed architectural description is an inherently time-consuming and costly endeavor, as it necessitates that the system design comprehensively addresses both functional and non-functional requirements. Given the complexity and breadth of such an undertaking, it is impractical to represent every nuance of the architecture in exhaustive detail. Nevertheless, [53] advocates for the use of multiple architectural views to effectively model the system. These views provide a structured approach to understanding and documenting the architecture:

- *Logical view*: This view illustrates the system's relationships in terms of objects or classes of objects, detailing their responsibilities and interactions. It provides a conceptual framework for understanding how various parts of the system function together to fulfill the system's requirements.

- *Process view*: This perspective focuses on the dynamic aspects of the system, depicting the runtime processes and their interactions. It is instrumental in understanding the system's behavior during execution, showing how processes communicate and collaborate to achieve the desired outcomes.

- *Development view*: This view dissects the software into components that are manageable for development. It illustrates how the software is partitioned for implementation, highlighting the division of work among individual developers or development teams. This ensures clarity in task allocation and facilitates effective project management.

- *Physical view*: This view maps the software components onto the hardware infrastructure, detailing the distribution of these components across system processors and physical devices. It provides insight into the deployment architecture, showing how software components are hosted on the hardware to ensure optimal performance and scalability.

The logical view is crucial for understanding the interactions between different parts of the system, defining their roles and responsibilities as objects or classes. This view aids in conceptualizing the overall architecture and identifying key components and their interactions.

The process view, on the other hand, emphasizes the dynamic behavior of the system. It illustrates how processes operate concurrently, communicate, and synchronize during execution. This view is essential for analyzing the system's performance, identifying potential bottlenecks, and ensuring efficient process management.

The development view provides a clear roadmap for the implementation phase, breaking down the software into modular components. It delineates the responsibilities of individual developers or teams, ensuring that each component is developed in a coherent and coordinated manner. This view is vital for managing the development process, tracking progress, and maintaining consistency across the project.

Finally, the physical view aligns the software components with the underlying hardware infrastructure. It details how the components are distributed across various physical devices and processors, ensuring that the system's deployment is optimized for performance, reliability, and scalability. This view is critical for planning the deployment strategy and managing the physical resources effectively.

In summary, architecture design is about systematically organizing the system's structure to meet both functional and non-functional requirements efficiently. By adopting a multi-view approach, as suggested by [53], developers can ensure that the architecture remains robust, maintainable, and adaptable to change. This structured methodology facilitates a comprehensive understanding of the system, guiding the development process and ensuring the successful realization of the system's objectives.

4.3.3 System architecture design and management

Based on the preceding explanations, this section delineates the architecture of the system, with a particular emphasis on a small-scale architecture viewed through a logical perspective. To facilitate comprehension and streamline the representation, a block diagram is utilized in place of Unified Modeling Language (UML) notation. In these diagrams, boxes are employed to symbolize the various components, and nested boxes are used to denote subcomponents, effectively illustrating hierarchical relationships. Arrows are incorporated to indicate the flow of data or control signals between the components, thereby elucidating the interactions and dependencies within the system.

The choice of a block diagram over UML notation is intentional, aimed at providing a clear and concise visual representation of the system's architecture. This approach ensures that the core elements and their interconnections are readily understandable, minimizing the complexity that often accompanies more detailed notational systems. By focusing on a logical view, the diagram highlights the structural organization and functional relationships between the components, offering a high-level overview that is critical for initial design and analysis.

Each component within the block diagram is strategically placed to reflect its role and significance within the overall system architecture. The arrows, denoting data or control signal flow, are carefully plotted to accurately represent the direction and nature of communication between components. This methodical arrangement aids in visualizing the system's operational dynamics, providing insights into how different parts collaborate to achieve the desired functionalities.

The hardware platform encompasses a diverse array of sensors, each necessitating meticulous management. To address this complexity, the architectural design strategically divides responsibilities among various components. As depicted in Figure 4.3, multiple sensors are interfaced via the Inter-Integrated Circuit (I2C) protocol. The *IO Control* application is tasked with overseeing the sensors connected to the I2C interface, ensuring efficient data acquisition and processing. Given that these sensors do not demand low-latency communication, their management can be effectively handled by an application running within the Linux kernel.

The architectural choice to utilize a Linux kernel application for managing these sensors is driven by the need to balance performance with system complexity. By leveraging the inherent capabilities of the Linux kernel, the system can handle the necessary data flows without imposing significant overhead or requiring real-time processing capabilities. This approach ensures that the sensor data is processed reliably and efficiently, contributing to the overall functionality and robustness of the system.

For the acquisition and processing of radar data, the *Radar App* is designated as the primary entity responsible for information retrieval. This application leverages a shared memory mechanism facilitated by OpenSTLinux, a strategic choice due to the radar sensor's connection to the Arm Cortex-M4 (M4) core. The M4 core is specifically selected to fulfill real-time data acquisition requirements, ensuring timely and accurate processing of radar data.

The shared memory mechanism employed by the *Radar App* enables efficient data exchange between the radar sensor and the processing application, minimizing latency and optimizing performance. This architectural decision capitalizes on the real-time processing capabilities of the M4 core, thereby enhancing the system's ability to handle high-frequency data input and complex computations inherent in radar operations.

The *Camera App* is tasked with managing the camera sensor, which is interfaced through the Digital Camera Memory Interface (DCMI) protocol. This application is meticulously designed to capture high-resolution images and process them for subsequent analytical purposes. The processing of the high-resolution images generated by the camera sensor necessitates robust computational capabilities, which are provided by the Arm Cortex-A7 (A7) core.

The *Camera App* is responsible not only for the initial capture of images but also for the subsequent processing required to prepare these images for analysis. The Arm Cortex-A7 core, known for its efficiency and performance, is ideally suited to handle the intensive processing demands associated with high-resolution image data. This processing includes tasks such as image enhancement, compression, and possibly initial feature extraction, ensuring that the captured data is in an optimal state for further analysis by downstream applications.

Once the images have been captured and processed, they are transferred to the *AI App* for further analysis. The *AI App* is responsible for executing advanced image processing algorithms and neural network models specifically designed to identify the Mediterranean fly.

The *AI App* employs sophisticated techniques to analyze the high-resolution images provided by the *Camera App*. This involves the application of complex algorithms that enhance the quality and detail of the images, facilitating more accurate identification. Furthermore, the *AI App* utilizes neural networks, which are trained to recognize the unique characteristics and patterns associated with the Mediterranean fly.

These neural networks leverage machine learning techniques to improve their accuracy and efficiency over time. By continuously learning from new data, the *AI App* enhances its ability to correctly identify the Mediterranean fly, thereby increasing the reliability of the system. The use of neural networks also allows the *AI App* to process large volumes of image data swiftly, ensuring real-time or near-real-time analysis.

The integration of the *AI App* within the system architecture underscores the importance of advanced computational methods in achieving precise and efficient identification of target species. By delegating the execution of image processing algorithms and neural networks to the *AI App*, the system ensures that the identification process is both thorough and accurate, leveraging state-of-the-art artificial intelligence technologies.

In addition to local data processing, the system necessitates connectivity to a cloud server for extended functionality, data storage, and remote access. This connectivity is facilitated by a Google client, which is implemented through the *Google IoT Client* application. The *Google IoT Client* is responsible for managing the communication link between the local system and the cloud infrastructure, ensuring secure and reliable data transmission.

The integration of the *Google IoT Client* within the system architecture allows for seamless interaction with cloud services, enabling advanced data analytics, storage solutions, and remote monitoring capabilities. This cloud connectivity is critical for leveraging the full potential of IoT (Internet of Things) applications, providing scalability, flexibility, and enhanced functionality.

To effectively decouple requests and responses between the various sensors and the Google client, the *System Server* application is employed. This application serves as an intermediary, managing the flow of data and commands, thereby isolating the sensors from direct communication with the Google client. This decoupling mechanism enhances modularity and simplifies the overall system architecture.

The *Event Manager* application is integral to monitoring the system's operations. It is responsible for logging activities, tracking the status of various processes, and issuing notifications when requests have been processed. This functionality ensures that all system operations are meticulously recorded, providing a comprehensive audit trail and facilitating efficient troubleshooting and system maintenance.

Inter-process communication (IPC) among all applications is facilitated via DBus, a message bus system that allows for the seamless exchange of messages between applications. DBus is particularly suited for this role due to its efficiency, reliability, and support for asynchronous communication, which is essential for the responsive operation of a complex, distributed system.

The initial architectural overview is depicted in Figure 4.6. In this schematic representation, the Google client is depicted as the entity responsible for managing communications with the cloud server. When a request is received from the cloud, the Google client interfaces with the *System Server*, which processes the request and responds appropriately.

By utilizing the *System Server* to mediate interactions between sensors and the Google client, the architecture ensures that each component operates within a clearly defined scope, enhancing the system's robustness and scalability. The *Event Manager*, with its comprehensive monitoring and logging capabilities, further augments the system's reliability by providing real-time oversight and detailed records of all operational events.

Figure 4.6 illustrates the interactions between the *System Server* and various sensor applications. Upon receiving a request, the *System Server* initiates a corresponding sensor request and notifies the *Event Manager* of this action. Once the sensor request has been fulfilled, the respective sensor application communicates the completion of the request to the *Event Manager*. Subsequently, the *Event Manager* either transfers the retrieved information or provides access to it, depending on the nature of the data.

For instance, in the case of the *Camera App*, instead of transferring the captured image directly through DBus, the application notifies the *Event Manager* of the image's storage location. This approach is adopted due to the limitations of DBus in handling large data transfers efficiently. Similarly, the *Radar App* employs the same method, indicating the location of the captured data rather than attempting a direct transfer.

Conversely, the *IO Control* application, which manages sensors connected via the I2C interface, directly transfers the measurement results to the *Event Manager* through DBus. This direct transfer is feasible because DBus is well-suited for transmitting basic data types, such as boolean, integer, or float values, ensuring efficient and reliable data communication.

All interactions with the *Event Manager* are meticulously logged and stored in a database. This logging mechanism provides a comprehensive audit trail, serving as a local backup that documents the system's operations and historical data. This log is invaluable for diagnostic purposes, system analysis, and maintaining an accurate record of system performance and interactions.

The *System Monitor*, as depicted in Figure 4.6, is responsible for overseeing various system resources, encompassing database size, stored images, radar data, processing resources, and application activity. This component continuously monitors these resources to ensure the system operates within predefined parameters.

Should the *System Monitor* detect that storage limits have been exceeded or identify any application failures, it promptly generates alarms and communicates these to the *System Server*. The *System Server* subsequently relays these notifications to the Google client, ensuring that critical issues are brought to the attention of remote monitoring and management systems.

Upon receiving a response from the Google client, the *System Monitor* takes appropriate action based on the directives provided. This may involve releasing certain resources to mitigate storage constraints or initiating recovery procedures to address and rectify application failures. The ability to dynamically respond to client instructions ensures that the system maintains optimal performance and reliability, even in the face of operational anomalies.

Figure 4.6 delineates the architecture for the firmware update process. This process is initiated by a request from the Google client. Upon receiving such a request, the *Firmware Update* application undertakes several critical tasks, including the downloading of the update, the partitioning of storage to accommodate the new firmware, and the application of the update itself.

Throughout this process, the *Firmware Update* application maintains continuous interaction with the *Event Manager* to ensure comprehensive logging of all operations. This interaction ensures that each step of the update process is meticulously recorded, providing a detailed audit trail and facilitating troubleshooting and verification.

The firmware update procedure is built upon the OTA by Mender framework, a robust and reliable over-the-air update solution. Mender's OTA framework offers several advantages, including secure and efficient delivery of updates, the ability to manage updates across a fleet of devices, and mechanisms for rollback in case of update failures. This ensures that the update process is both reliable and resilient, minimizing downtime and maintaining system integrity.

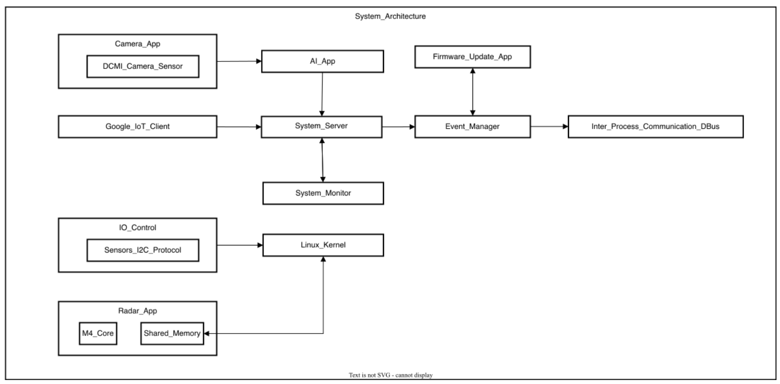


Figure 4.6: Software architecture and management for the appplications running on the SoC.

4.3.4 Structural model of the software system

The depicted structural architecture represents a layered IoT system integrated with Google Cloud IoT Core, and it features multiple components that work together to achieve specific functionalities. The topmost layer showcases the Google Cloud IoT Core, which is responsible for cloud connectivity and IoT functionalities. Communication between the local system and the cloud is facilitated using the MQTT protocol.

Below the cloud layer, the architecture comprises several middleware applications: Event Management, System Server, Cloud IoT Client, System Monitor, and SQLite. Event Management handles system events and logs activities, ensuring comprehensive audit trails. The System Server acts as an intermediary, managing data flow and commands between various components, thereby enhancing modularity. The Cloud IoT Client manages secure and reliable communication between the local system and Google Cloud IoT Core. System Monitor oversees system resources and application activities, generating alarms for any detected issues. SQLite serves as a lightweight database, supporting local data storage needs.

The application layer includes specialized applications such as Camera App, I/O Control, Firmware Update, User Management, and AI App. The Camera App manages camera operations and preprocessing functions, capturing high-resolution images for analysis. I/O Control interfaces with various sensors connected via the I2C protocol, managing sensor data acquisition and processing. The Firmware Update application handles the firmware update process, ensuring the system firmware remains up-to-date through over-the-air (OTA) updates. User Management handles user authentication and authorization. The AI App executes advanced image processing algorithms and neural networks for identifying the Mediterranean fruit fly, performing preprocessing functions to prepare images for analysis.

The foundational software layer, labeled as BSP Components, includes the Filesystem, Linux Kernel, and Boot Chain. The Filesystem manages file storage and organization. The Linux Kernel, as the core operating system component, provides essential services and interfaces for hardware interaction. The Boot Chain consists of the First Stage Boot Loader: Trusted Firmware-A, responsible for initial hardware initialization, and the Second Stage Boot: U-Boot, which manages subsequent stages of the boot process and transitions to the Linux kernel.

Overall, the architecture ensures efficient and reliable operations through a well-organized, layered approach, promoting modularity, scalability, and ease of maintenance.

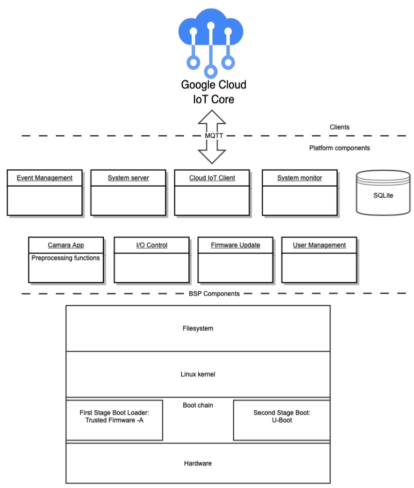


Figure 4.7: Structural architecture of the software system.

Chapter 5

Results and analysis

5.1 Radar-Based detection and counting of fruit flies

Radar is the most popular technique among remote sensing solutions [46] because the information is present in the radar signal's intensity, frequency, phase, and modulation [18]. Compared to other remote sensing techniques, such as infrared or ultrasound, radar is, most of the time, not sensitive to light, color, sound, acoustic noise, or temperature, as shown in Table 5.1.

The radar also has been applied to insect study since the 60s, and this application is known as *radar entomology*. Conventional entomological radars are non-coherent, and the signal amplitude and polarization information received from the insects are used to detect aerial insects' density and class [31]. This type of radar operates at a wavelength of 3.2 cm in the X-band and uses a parabolic antenna with a beam width of one to two degrees. Coherent radars offer better measurement accuracy [3]. With this type of radar, both amplitude and phase

	Sensibility			
Sensor	Temperature	Color	Light	Sound/Noise
Infrared	Yes	Yes	Yes	No
Ultrasonic	Yes	No	No	Yes
Radar	No	No	No	No

Table 5.1: Comparison of remote sensing technologies.

information can be used to extract the micro-Doppler frequency induced by the vibratory components of the target. Coherent radars operating the W band are the ones that achieve the best performance in measurement precision and also the smallest measurable size of the insect [13].

Particular challenges that emerge when the radar is applied in entomology are primarily associated with issues originating from the backscattered signal. These drawbacks include, among others: intensity decay, absorption (or complete blockage), scattering (additional reflections), refraction (change of direction caused by the shift in medium), and drift (caused by lateral movements of the medium). The measurement context is another variable that produces problems with radars, for example, when insects settle or crawl on vegetation surfaces. However, this problem can be solved with visual methods such as image analysis. Despite all these limitations, radar continues to be one of the most effective tools for observing insect flight because it works in severe weather conditions and round-the-clock [13].

In the case of radar entomology, it can be focused at the individual or group level on aspects such as migration, behavior, target characterization, and surveillance [13]. For these applications, it is customary to use radars of type scanning, vertical looking (VLR), harmonics, or frequency-modulated continuous wave (FMCW) [42].

The signals provided by the radars are used to estimate the parameters of an isolated insect [32]. For example, to calculate the mass of an insect, in [2] the authors proposed in 1989 to use the radar cross-section of the insect (RCS) since it was observed that there was a logarithmic relationship between the mass of the insect and its average RCS [2]. The RCS quantifies the target's backscatter and characterizes how much of the transmitted signal was intercepted by the target; it depends not only on the material's properties but also on the frequency, polarization, orientation, geometry, and angle of incidence of the transmitted wave [26].

Another parameter that can be determined using the radar is the target's orientation, which according to Long [31], can be calculated using the polarization pattern; the power of the received signal reaches its maximum value when the polarization direction is parallel to the axis of the insect's body. This principle has been shown to perform well for *vertical-looking* type radars (VLR). The wing beating is another parameter that can be calculated using radars, such as radars in the W band. The wing beating causes a fluctuation in the amplitude of the radar signal, producing a periodic modulation and, therefore, it can be used to detect and characterize the wing beating [57].

Other application of radar is insect tracking, which is carried out using the *harmonic radar* technique, which consists of attaching a small transponder to the insect and excite it with the radar to re-emit a new signal at a different frequency [5]. This application has been widely used to study the movement of insects in plantations, such as the study of the displacement of the melon flies, *Zeugodacus cucurbitae*, which are major pests and pose invasion risks [37] or *Vespa velutina*, which preys on pollinating insects [33]. For honeybee surveillance, Nawaf et al. [1] used a 5.8 GHz Continuous-Wave radar to monitor free fly activity. Using machine learning techniques, the authors were able to automated classification of the different activities such as leaving, entering, and hovering.

For insect migration and early detection, the *vertical-looking* radar (VLR) is used. For example, Chapman et al. [4], the authors used a VLR for monitoring migrant insects populations. Rotating the polarization of the radar and nutation, Chapman et al. were able to detect different insects in the air at different altitudes. A database of migration flux was created for different species. In a similar work, Wang et al. [59] also used a VLR to detect different insects in the air but focused on ascent and descent behaviors. Without specify the species, the author was able to detect insects with mass less than 10 mg.

A big problem with radars is related to measurement; small insects reflect radiation that can be hardly observable and, therefore, tricky to interpret. This condition is especially true as the dimensions of the insect become around or less than 5 cm [61]. Measurement is affected not only by size but also by the aspect and relative orientation of the target to the antenna, which directly impacts a small RCS magnitude [13]. Another factor affecting the RCS is humidity, a main reflective component. Hajovsky et al. in 1966 [17] reported that the loss of body moisture affects insects' dispersal properties; the humidity decreased considerably after their death.

Searching the recent literature, different studies have been reported for insect measuring with size dimension smaller than 5 cm. Rui et al. [58] used a X band and Ku-/K band radars to detect different types of moths. Using the RCS, the authors were able to classify the mass and body length. For mass estimation, the authors reached twice the precision compared with traditional methods. For body length, the authors were able to measure body length from 6 to 28 mm using a range of frequencies from 4 to 38 GHz. A similar study was conducted by Wang

[20], where the use of support vector regression (SVR) was proposed to estimate the mass of different moth species. In the experiment, the authors used a X-band radar and an microwave anechoic chamber where the moth was attached to a polyethylene line suspended. The size for the different species was not reported.

Continuing with body width and length estimation, Li et al. [28] used a X-band polarimetric radar to estimate the body width and length of different insects. The authors took 159 insects from different sizes and split them in three groups. For small insects, the sizes were in the range of 10 to 20 mm, for medium insects, it was 20 to 30 mm, and for large insects, the size ranged between 30 and 47 mm. They propose empirical equations based on the different RCS parameters to estimate the body width and length of the insects.

Riley [48] using an X-band radar and a transmission line to prevent beam scattered, was able to measure tiny insects (less than 1 cm). Another one was conducted by Wang et al. [57], where it was possible to measure different targets of the species *Mythimna separata* of sizes 10-42 mm using FMCW radars in the W and S bands. For free fly insect monitoring, Diyap et al. [10] used a continuous wave radar in W-band to detect two species: mosquitoes (*Culex pipiens*) and bees (*Apis mellifera*). In both cases, due to the dimension of the insects, the authors used *micro-Doppler* effect generated by wing-beat to detect and classify the species. Simulation and experimental results validated the proposed method.

The Table 5.2 shows a summary of the different studies reported in the literature. As it can observed, the different studies are focused on the estimation of the insect size, mass, body width and length, surveillance or tracking. Also the setup required to measure the insect is heavy and not portable. In this sense, the use of anechoic chambers and heavy equipment was reported. The size of the insect is not reported in all the studies, but the smallest insect was 10 mm. Regarding to the species, the most common insects are moths, and bees. The most common radar used is the X-band, Ku-band, and W-band. For the radar type, mainly FMCW, VLR and CW are used.

Reference	**Radar Type**	**Band**	**Application**	**Insect Species**	**Dimensions**
[57]	Coherent	W (93.6 GHz) and S (3.3 GHz)	Wing-beat detection	*Mythimna separata*	10-42 mm
[5]	Harmonic	X (9.4 GHz)	Tracking	*Vespa velutina*	20 mm

Reference	Radar Type	Band	Application	Insect Species	Dimensions
[1]	CW	C (5.8 GHz)	Surveillance	Honeybees (species not reported)	Not reported
[59]	VLR	Ku (16.2 GHz)	Detection and tracking	Various insects	Not reported
[58]	Multifrequency	X (8.25–11.75 GHz), Ku (17.75–18 GHz), and K (18–23.75 GHz)	Morphological parameter estimation	Various moth species	6-28 mm
[20]	SFCW	X (9.4 GHz)	Mass estimation	Various moth species	Not reported
[28]	Polarimetric	X (9.4 GHz)	Width and length estimation	Various insect species	10-47 mm
[48]	-	X	-	Aphids and planthoppers	Not reported
[10]	CW	W (94.3 GHz)	Wing-beat classification	*Culex pipiens* (mosquitoes) and *Apis mellifera* (bees)	Not reported

Table 5.2: Summary of the different studies reported in the literature on radar-based insect detection.

The utilization of the W-band radar remains uncommon in entomology; however, the findings presented in this section create new prospects for applying this technology for detecting small insects. The proposal shows the potential of using the radar for counting, which is new in the literature for radar entomology. Regarding *smart traps*, we found no reports on the use of radar [23, 43, 44, 40]. So the present research is the first proposal and validation for its implementation.

5.1.1 Materials and methods

The experiment's arrangement is shown in Figure 5.1. The radar was placed in the center of a structured aluminum cube with dimensions of 30x30x30 cm, pointing towards its base. The cube's walls are constructed with transparent acrylic to prevent flies from escaping, and the cube has a door to access the inside. A 2 cm thick polystyrene base was used to place the target, providing mechanical stability and preventing the radar from being affected by the material's reflectivity. The polystyrene base was used because it is a material that does not affect the signal received by the radar since it has a low reflectivity [57].

The W-band pulsed radar used was the Acconeer©A111 (as it was proposed in the previous sections), with an operating frequency of 60.5 GHz and a spatial resolution of 5 mm. That means covering a distance of 30 cm, the radar will transmit 600 pulses to sweep the distance range and generate the corresponding data points. The radar provides two primary *services*: the *Envelope Service* and *IQ Service*. The Envelope Service provides the envelope of the received signal, which is the amplitude of the received signal as a function of distance. The IQ Service provides the in-phase and quadrature components of the received signal. They can be used to compute amplitude and phase. Only the Envelope Service was used in this research.

Figure 5.1: Experimental arrangement to fix the radar for the detection of insects.

The following parameters were used to configure the radar. The first parameter was antenna gain, which can be adjusted between 0.0 and 1.0. The recommended value for this parameter is 0.5; however, for the proposed experiments, the measures started with 0.1 and the value was increased gradually to avoid saturation of the ADC converter. Saturation happens when the reflectiveness of the material is too high with the gain set, so the API will automatically detect this condition and according to the documentation provided, the ADC's gain should be reduced to have a right measurement. The second parameter was the hardware acceleration average sample (HWAAS), i.e., the number of averaged samples used to obtain a single measurement. This parameter is used to reduce the signal noise. For this experiment, an initial value of 15 was used; the initial value recommended by the radar manufacturer. The third parameter was the power save mode, which reduces the radar's power consumption. For this experiment, it was disabled to obtain the best possible performance. The fourth parameter was the update rate, which is the number of frames obtained per second. A frame is just the data for a complete azimuthal sweep up to maximum range . For this experiment, the default value of 30 Hz was used. The fifth parameter was the profile, which controls the length of sent pulses and how they are sampled on return. The max resolution profile was used for the experiments, which is recommended for close range (less than 20 cm). Finally, the sixth parameter was the range set between 10 and 26 cm. This parameter controls the range of distances at which the measures are taken.

One thousand sweeps were performed to obtain a single final measurement and then averaged to minimize the impact of noise. This procedure for noise diminishing is justified because the object is at a fixed distance, and the noise where the signal is immersed has zero mean. So this will help to avoid errors with the interpretation of object distance. All the experiments were conducted with this condition.

Based on the works reported by Wang [57] and Riley [48], for the first experiment this did not use lenses or any other radar accessories. However, it was found that the antenna gain was low and dispersed, so according to Riley's [48] proposal, this led to add a lens to improve the antenna gain and concentrate better the signal beam. The lenses used were from Acconeer: Fresnel (FZP) and a Hyperbolic lens (HBL), both made of solid polyamide PA12. Each of these lenses has a gain dependent on the position in which they are placed on the *printed circuit board* holder (PCB). Table 5.3 summarizes the gain and angle (in the horizontal and vertical planes) of the signal beam as a function of the lens used.

The target was modeled using metal spheres of different sizes to characterize

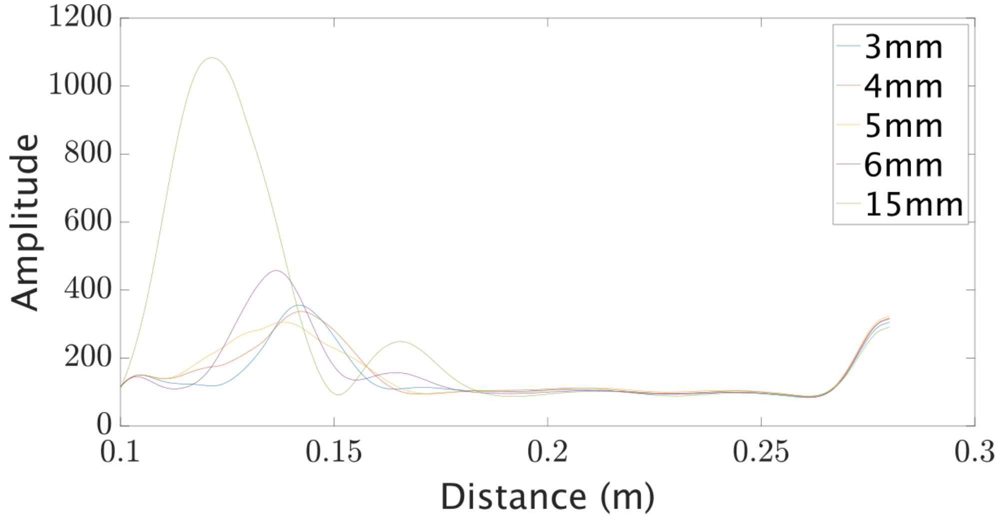
	Max. Gain (dBFS)		HPBW-E (degree)		HPBW-H (degree)	
	D1	D2	D1	D2	D1	D2
HBL	11.6	20	22	17	30	15
FZP	11.4	18.2	20	12	27	12

Table 5.3: Gain reported by the manufacturer in the vertical (E-Plane) and horizontal (H-plane) planes according to two lens positions on the holder (D1, D2). Source, manufacturer data sheet.

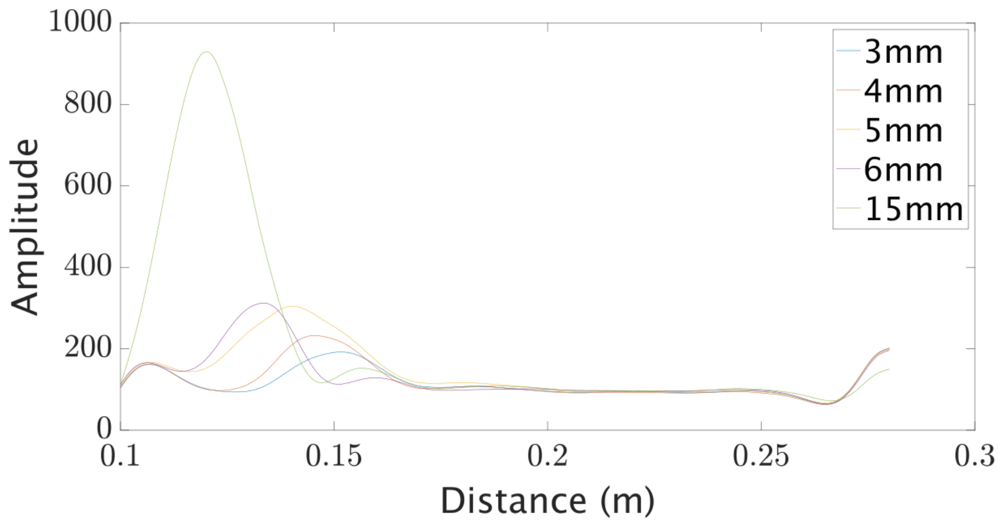
the radar and determine the presence of a target. According to Drake [13], metal spheres or water drops are the ideal models that can be used for insect representation due to their high reflectivity. For this purpose, metal spheres were placed in polystyrene support and at a distance of 13 cm from the radar; since the minimum distance suggested by the manufacturer is 10 cm. The used sphere sizes were 3, 4, 5, 6, and 15 mm in diameter. Figure 5.2 summarizes the obtained results for each sphere, reaching a minimum detection with a sphere of 3 mm.

A *radar detection* happens when the received signal exceeds a particular threshold value. Three parameters are associated with the detection: probability of detection (P_d), probability of missing (P_m), and probability of false alarm (P_f). The P_d is the probability that the radar detects a target when it is present. The P_m is the probability that the radar does not detect a target when it is present. The P_f is the probability that the radar detects a target when it is not present. The P_d and P_m are related to the radar's sensitivity, and the P_f is related to the radar's noise level. To increase P_d, the *signal-to-noise ratio* (SNR) must be increased. The SNR is the ratio of the signal power to the noise power. In the experiment, the noise level was measured without the presence of a target. Calculating the variance for noise level, it was observed that it was below 200 using the polystyrene base. With this condition, the threshold value was choosen to produce the results in Figure 5.2. This assumption is true due to the fact that the noise level is zero mean, and the variance is the square of the standard deviation.

Another experiment used an identical metal sphere of 5 mm to continue with the radar characterization. For this purpose, a matrix of holes over a polystyrene base was used. Each hole had a diameter of 3 mm and a separation of 1 cm; all



a)

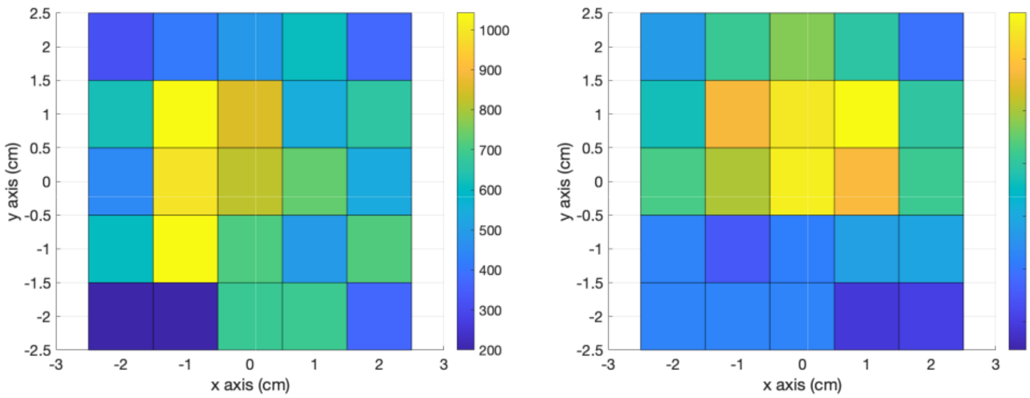


b)

Figure 5.2: Radar intensity for FZP (a) and HBL (b) lenses. X and Y axis in cm.

were drilled with a CNC machine to obtain good precision between holes and avoid misalignment between measures. A 5 mm sphere was used as a target because this almost matched the size of medflies and was placed in the orifices to determine the radar's detection zone. The measures ranges were in a 5x5 cm area, taking the center of the radar as a starting point (0,0). One thousand frames were sampled and averaged for each hole to obtain a single measurement. Figure 5.3 shows the experiment results, wherein the axes X and Y represent the distance from the center of the radar, and the amplitude of the maximum received signal is in the

Z axis.



a) **b)**

Figure 5.3: Radar intensity for FZP (a) and HBL (b) lenses. X and Y axis in cm.

The results showed that radar has a detection zone of 1.5x.1.5 cm, close to the center. Here it is important to note that for declaring the detection of a sphere, a threshold value was set to 200 after measuring the noise level of the radar (same as first experiment) , so the results over that value are considered as a sphere presence, and below that value, an absence. For absence values, those were normalized to 200 to visualize the results better. Once the detection of metal spheres and the minimum achievable resolution have been validated, the same experiment was carried out with Mediterranean flies. Figure 5.4 shows the experimental setup for a Medfly placed in the center of the base. In the beginning, dead flies were used to prevent movement; however, no detection was observed. This result was already reported by Drake [13], which was corroborated since the dead flies did not present reflectivity due to the low moisture content of the dead bodies; so live flies were used in the following experiments. These tests were carried out in the dark to avoid movement, but even under these conditions, the flies showed activity, which made detection difficult. Figure 5.5 shows that the Medfly is detected by increasing the magnitude of the received signal that exceeds the detection threshold set at 200, which was determined by measuring the signal received in the open air.

Figure 5.4: Radar experiment setup with dead Medfly.

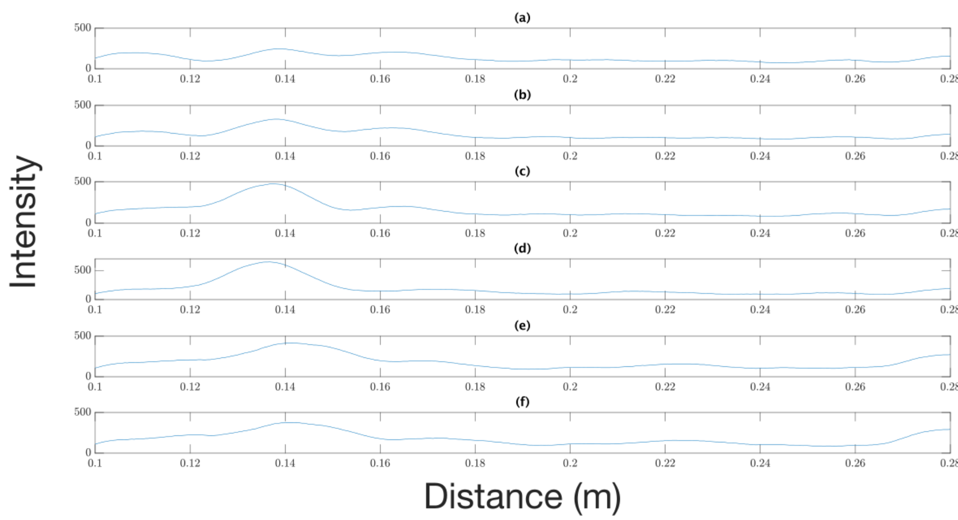


Figure 5.5: Radar detection for Mediterranean fruit fly. Graphs a) and b) show the radar intensity before the detection threshold. Graphs c) and d) show the radar intensity after the detection threshold when the fly is in the detection zone. Note the increment in the intensity values by 0.14 m. Graphs e) and f) show the radar intensity after the detection when the fly moves away from the radar detection zone.

Given the difficulty of detecting live flies, another experiment was designed to validate the detection. According to Drake [13], carbon dioxide or cold is recommended for anesthetized live insects. In the experiment, the temperature of the flies was reduced to 4°C for 3 minutes to loosen their movements. However, this was ineffective, as not all flies survived the low temperature. While detection was still possible, the received signal was weak. A new experiment was designed to solve the above problem and to validate the detection based on the field conditions in which the Medfly is captured. For this, a literature search was carried out, and it was found that one of the primary Medfly capture techniques is using traps [38]. Although there are many traps, delta traps are used primarily in Mexico. This trap type has a triangular prism shape, with a glue base and a grid at the top where the attractant is placed. Figure 5.6 shows a delta-type trap. Therefore it was decided to use the glue base as a reference point for a new detection experiment. For this, the same polystyrene base was used on which the glue base was placed. The same procedure was used for the metal spheres to measure the reflectivity of the glue base. Still, in this case, it was done with the two available lenses (FZP and HBL) and in different positions to vary the gain according to Table 5.3. It is crucial to characterize the glue base with the two lenses since the amount of glue is not uniform, and it affects the reflectivity obtained by the radar. In the experiment, the same glue base was used during all the measurements to avoid variations in the graphs presented. Once the bottom was characterized, flies were added to the glue base, and measures were taken with the lenses. Two measurements were added with the variation of two parameters: HWAAS and gain. Measurements were made with the gain values of 0.1, 0.2, and 0.3. In the case of HWAAS, the values 15, 30, and 40 were used. As a result, three measurements were made for each lens and position with the parameter variation mentioned above.

Figure 5.6: Delta trap used for Medfly capture.

5.1.2 Results

The Figure 5.7 shows the different measurements of the backscattered signal using different bases and with the presence of a fly. In this conditions, the fly cause an interference compared with the reference signal and the *shadow effect* of the fly over the reference shows an improvement in the detection. For example, for Fresnel lens (Figure 5.7a) the signal is 11% less than reference, but much stronger than signal with polystyrene base.

Figure 5.8a (top left corner) shows the graphs obtained for the FZP lens in position 1 with a gain of 0.1 and HWAAS of 15. It can be seen that the reflectivity of the glue base is the highest of all the measurements made, which corresponds to the expected result. Adding one and two flies decreased reflectivity. By increasing the gain of the amplifier and HWAAS to double (0.2 and 30, respectively), the same behavior is observed. In the case of the gain of 0.3 and HWAAS of 40, the radar's ADC was saturated, so these results were not considered in this report.

Repeating the experiment for the FZP lens in position 2, the results are similar to those obtained in position 1; however, the reflectivity is higher due to the gain increase. Similarly, the data obtained for the gain of 0.3 and HWAAS of 40 were discarded due to saturation. The results are shown in Figure 5.8b (top right corner).

In the case of the HBL lens in position 1, glue base reflectivity is lower than that obtained with the FZP lens and decreases only up to the first fly, slightly increase for the second. When doubling the gain and HWAAS, the results are similar to those obtained with the FZP lens, as shown in Figure 5.8c (bottom left corner). The radar was saturated for a gain of 0.3 and HWAAS of 40, so these results were not considered. With the highest gain in position two and the HBL lens, the reflectivity increased above all measurements. Still, the results were maintained, where the reflectivity decreases for second fly. These results held for 0.2 gain and 30 HWAAS, but the radar saturated for 0.3 gain and 40 HWAAS. The results are shown in Figure 5.8d (bottom right corner).

After the measures were taken, a decreasing pattern was observed in all cases, so no more measures were considered due to this pattern.

5.2 Sensor performance: TVOC and eCO2 detection

The advent of Precision Agriculture (PA) tools has ushered in a new era, enabling farmers to analyze the spatial-temporal variability of several critical factors that influence plant health and productivity. Data collected through sensors are stored

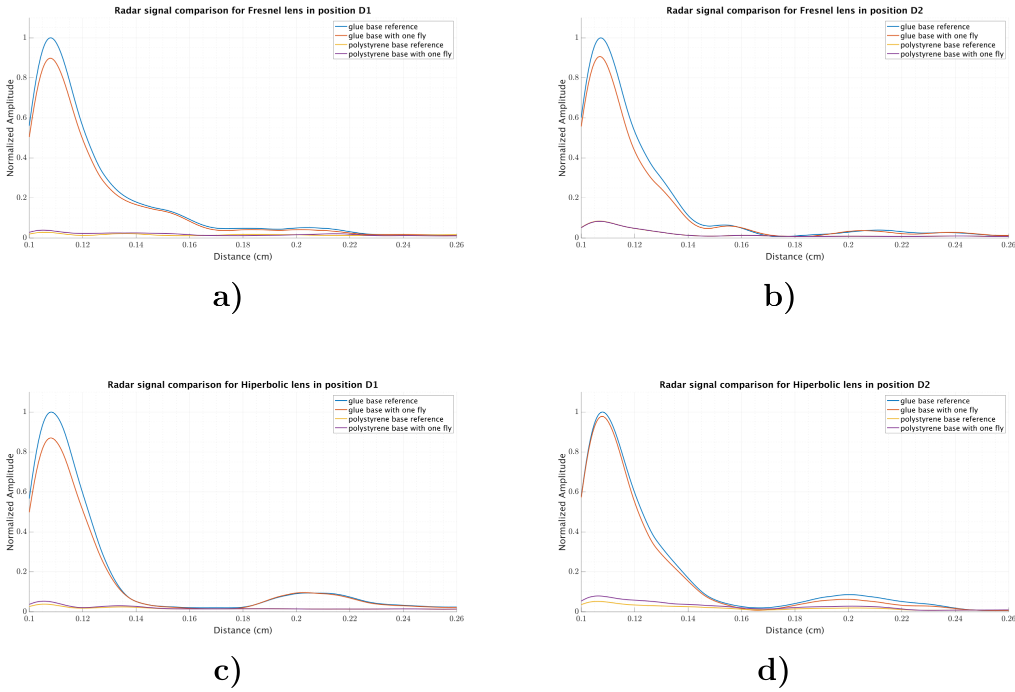


Figure 5.7: Results for radar measurements using polystyrene and glue bases.

and synthesized to guide decision-making processes and implement early warning systems to mitigate threats [3]. Additionally, there has been a shift towards *smart traps*, which enhance traditional methods by improving the accuracy of insect counting and detection capabilities. This transition is driven by the demand for more efficient, less labor-intensive techniques that allow for continuous monitoring and data collection [35].

Advancements in sensor technology and microprocessors have revolutionized the development of new devices that facilitate the detection and monitoring of insect pests over extensive areas at reduced costs and deployment times. These innovative devices, integral to early warning systems, continuously monitor the pest community and its quantitative distributions, helping to avert potential agricultural disasters [21]. Although integrating such technologies involves multiple disciplines, the benefits are substantial [21].

Modern sensors can be seamlessly integrated with the Internet of Things (IoT) or directly connected to cloud-computing services, enhancing decision-making processes by enabling real-time surveillance at the field level [3]. This connectivity allows for immediate data analysis and response, crucial for managing dynamic

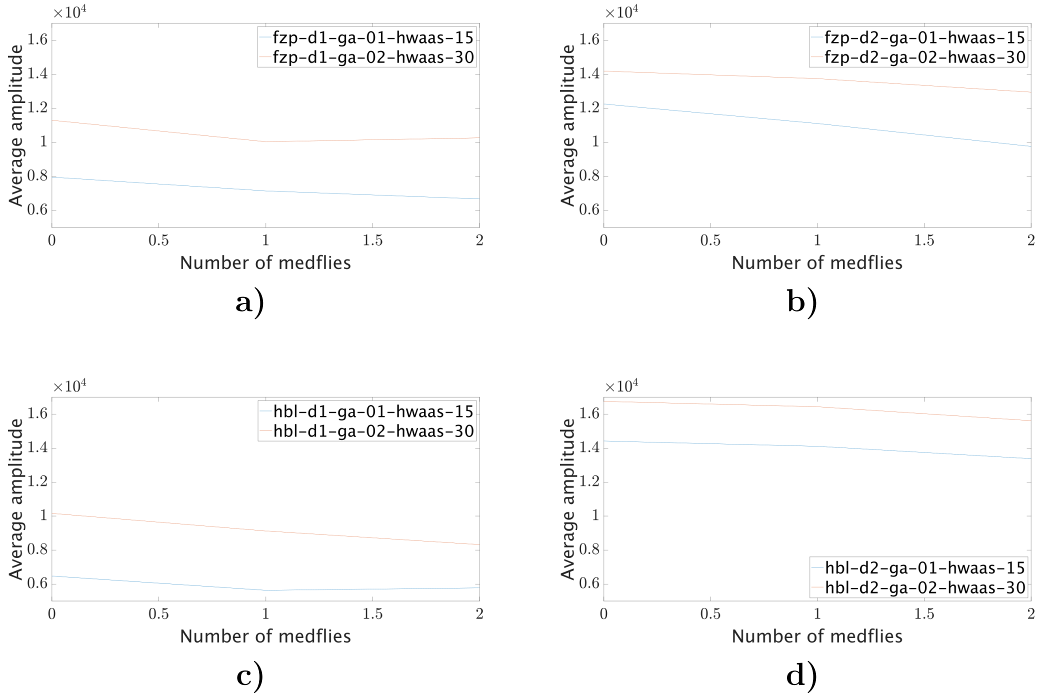


Figure 5.8: Results for medfly counting using different lens positions, gain values and HWAAS. Graphs (a,b) correspond to the FZP lens in position 1 and 2, respectively. Graphs (c,d) correspond to the HBL lens in position 1 and 2, respectively.

pest populations effectively.

Moreover, the application of new technologies extends beyond traditional monitoring methods. Examples include radar technologies that track pest migration patterns [4], video equipment for observing flying insects, thermal infrared imaging to detect heat signatures, and chemiluminescent tags to track insect movements in darkness [9]. These tools not only improve the accuracy of pest detection but also contribute to comprehensive field surveys across various pest species, supporting more targeted and effective pest control strategies.

Different traps and sensors have been applied for pest monitoring. For instance, to monitor the moth *Cydia pomonella*, Guarnieri et al. [15] developed a system modifying a trap used in the field with a mobile phone to capture and report the data; the data were sent to a remote server where images were analyzed. The sound produced by *Rhynchophorus ferrugineus*, a palm tree pest was digitally processed to generate the sound spectrum and detect its presence when the pest eats or moves [36]. Similar works based on sound recording were reported in [41, 12] for detection and classification of pests. Robot cars have been used to monitor pests of Pyralidae species [3]. Liu et al. [30] mounted an image-processing system in a robot car to detect and count the number of moths in the field, reaching an accuracy of 95%. For the *Mythimna separata* species, Wang et al. [57] used a radar system to detect their presence and wingbeat, being able to detect insects with a length of 10-42 mm using FMCW radars in the W and S bands.

Regarding to Mediterranean fruit fly, in 2019 the losses attributed this pest in Brazil amounted to 120 million USD, severely impacting exports to Japan, the USA, and Chile [40]. Generally, pest control relies on pesticides, whose efficiency depends on timely and precise location information about infestations.

Trap monitoring for Mediterranean fruit fly, it is essential in pest detection, suppression, and eradication programs worldwide, typically involves olfactory and possibly visual stimuli to attract adult species. Most attractants are food-type, emitting ammonia and simulating protein sources [51]. However, maintaining a trap network is costly, considering the required monetary, human, and material resources. Staff typically check traps weekly, traveling long distances to areas that may be difficult to access, which delays information flow [11, 14]. The information on pest species and densities is primarily acquired through visual inspection, which complicates monitoring population dynamics due to the relatively low sampling rate. Smart traps address these issues efficiently by identifying and counting pests as they enter the trap, allowing for faster information flow [60].

5.2.1 Sensors on smart traps for Mediterranean fruit fly

Different technologies have been applied to monitor and capture the Mediterranean fruit fly. Potamitis et al. [43] modified a McPhail trap, adapting an optoelectronic sensor to monitor the fly entrance by sensing wingbeat. The goal was to analyze the generated optoacoustic spectrum, reaching an accuracy of 91% in detection. An updated version of the system integrates a bimodal optoelectronic sensor and stereo recording [44], showing that it was possible to distinguish between fruit fly species (*Ceratitis capitata* and *Bactrocera oleae*) with an accuracy of 98.99%. Image capture is robust and can be used for entomologists or image processing systems for decision-making. Therefore, camera sensors have been also used in smart traps. Doitsidis et al. [11] developed a system based on a McPhail trap modified with a camera that monitored *Bactrocera oleae* and allowed remote access to the images, reducing the time spent in collecting data. The system does not add automatic image recognition; expert entomologists analyze the images. In a similar way, Shaked et al. [51] created two systems, one to monitor *Ceratitis capitata* and another for *Bactrocera oleae*, *Dacus ciliates*, and *Rhagoletis cerasi*. Both were based on a real-time surface image sent to a remote server for image analysis, reaching 88% of accuracy. Haff [16] uses hyperspectral images to classify the spots of the fruit fly in mangoes. The images were analyzed using Gaussian blur radius, ball radius, and minimum particle size techniques. However, the main issue of the system is the cost and size of hyperspectral cameras, making it an impractical solution for the field. Recently, Diller et al. [8] created a surveillance system based on a McPhail trap modified with a camera and Raspberry Pi Zero for trapping and wireless transmission of images to the cloud. Based on a Deep Learning (DL) model, a precision of 93-95% in the species identification is reached. Similarly, Uzun [56] reported in the training of deep learning algorithms to detect and count the *Ceratitis capitata* in the field. The algorithm was trained with 722 images and 150 for validation. The algorithm detected and counted the species with an accuracy of 99.5%; however, no hardware was embedded in the trap for capturing images.

Other types of sensors have been integrated into smart traps, presenting innovative approaches for pest detection. Kalamatianos et al. [24] equipped a McPhail-type trap with a system that included different instruments, such as wind and temperature sensors, WiFi, and a GSM modem. The system gathered data from the field and used a public pre-trained toolkit for identifying the species *Bactrocera Oleae*. With this information, an automatic classification of the species using different convolutional neural networks (CNN) reached an accuracy of 91.5%. In [23], a system based on sensors operated remotely in a McPhail trap was implemented. The capture module used a double infrared sensor placed in line to validate that the fly enters the trap through a tunnel designed to let in only Mediterranean flies. A microcontroller (MSP430F449) was responsible for processing GPS information, temperature, humidity, and wind speed; a *Host Control Platform* (HCP) received commands through a GSM module to information be processed and stored in a SQL table using LabView©. An improved mechanism that prevents double-counting depending on the route that flies follow inside the trap was proposed by Liao et al. [29]. The system implements nodes equipped with ZigBee modules to cover extensive and difficult-to-access areas the GSM network does not cover. In this way, the information from the nodes can be transmitted to a gateway that sends data to the HCP.

Infrared sensors have also been used to measure wing beat in McPhail traps, as proposed by Potamitis et al. [43]. The captured signal passes through an analog-digital converter (ADC) which delivers a signal in time and amplitude to which a fast Fourier transform (FFT) is applied to characterize the spectrum in frequency. With this, it was possible to identify the Mediterranean fly and different species. In a subsequent work [44], the light from the infrared LED is passed through the Fresnel lens and collimated. The wings beating of the insect cast a shadow on the opposite receiving Fresnel lens. The collimated light is partially dispersed laterally at 90°and directed to the passive Fresnel lens that records the reflected light. Finally, a dark cone-shaped plastic fixes the LED and photodiodes to their correct focal point. A mixture of infrared and sound sensors was implemented by Sandrini et al. [50]. The infrared sensor measures wing beat while the signal amplifier output of the sound sensor is connected to the input of a sound card. The beating signal was recorded. A time and frequency analysis determined the main components and characteristics that identify each species. Recently, Hernandez et al. [19] used a radar system to count the number of fruit flies captured in a trap. The radar system was able to detect the fruit flies using the shadow effect, which changes the radar intensity when the Mediterranean fly is inside the trap, demonstrating an efficient approach to solving pest detection.

The literature review shows that integrating different sensors strengthens the systems to monitor and detect Mediterranean fruit flies. However, research on new sensors in smart trap systems applied to fruit fly detection is still in development, and several challenges must be addressed. One of the various components of this kind of trap is the lure, which plays a vital role in the capture of insects. Commonly, the lures are based on volatile organic compounds (VOCs) that attract the insect to the trap when released into the air.

Trimedlure, a synthetic lure consisting primarily of four trans isomers, is highly effective in attracting male Mediterranean fruit flies . This lure is considered superior to many other synthetic and natural attractants, owing to its unique configuration and potent behavior-inducing properties [22]. Although specific data on its longevity under various environmental conditions are not detailed, the molecule's effectiveness is sufficiently sustained for widespread use in traps for surveying and controlling medfly populations [22]. Trimedlure is classified as Volatile Organic Compounds (VOCs) due its structure incorporates volatile elements that allow it to evaporate and disperse into the air, a characteristic behavior of VOCs, enhancing its effectiveness as an aerial dispersant.

However, the VOCs are unstable and can be degraded by environmental factors such as temperature, humidity, and light. So, without an active lure, no capture is possible, and the trap is useless. Currently, the only information about the useful life of the lure is provided by the manufacturer based on reference conditions. Therefore, obtaining information about the lure lifetime is essential to keep the trap network in optimal conditions, according to regional and weather conditions.

This section explain the use of air quality sensors to monitor and detect the trimedlure. Two sensors were used to show the potential of this approach: the *SGP30* and *ENS160*. The sensors measure the air concentration of VOCs (volatile organic compounds) (TVOC, Total VOC) and the air carbon dioxide concentration (eCO_2). The integration of air quality sensors showed promising results as an aid tool that could be implemented in new smart trap systems to improve the information gathered and reduce trap visits to replace lures.

5.2.2 Sensors and hardware setup

Volatile Organic Compounds (VOCs) are ubiquitous in both indoor and outdoor environments, with over 5,000 different types identified, many of which are harmful to human health and the environment [25]. The ability to monitor VOCs accurately is crucial due to their potential adverse effects. Various sensors are available that can detect changes in gas concentrations, facilitating data collection for further analysis and decision-making. For instance, Photoionization Detectors (PID) utilize ultraviolet light to ionize gas molecules, allowing for the detection of VOCs by measuring the resultant charge carriers. Flame Ionization Detectors (FID), commonly used in industrial applications, detect hydrocarbons by burning them and measuring the ions produced. Metal Oxide Semiconductor (MOS) sensors detect specific compounds like benzene, ethanol, and toluene by changes in resistance across a thin metal oxide layer. It is important to note that some VOC sensors require temperature compensation for accurate readings, though this feature may not be integrated into all sensor models [7].

Carbon Dioxide (CO_2) is a colorless and odorless greenhouse gas. Its concentration, typically around 400 ppm in ambient air [45], can be measured using various sensing technologies. Nondispersive Infrared (NDIR) sensors determine CO_2 levels by detecting the amount of infrared light absorbed at a specific wavelength (4.3 μm). Photoacoustic spectroscopy involves exposing a gas sample to electromagnetic energy tuned to CO_2's absorption wavelength, then measuring the resultant pressure waves with an acoustic detector to calculate the gas concentration. Electrochemical sensors detect CO_2 by measuring the current change when CO_2 reacts with a polymer surface inside the sensor. Additionally, Metal Oxide (MOX) technology utilizes a thin film that alters its resistance in the presence of CO_2, providing a measure of gas concentration.

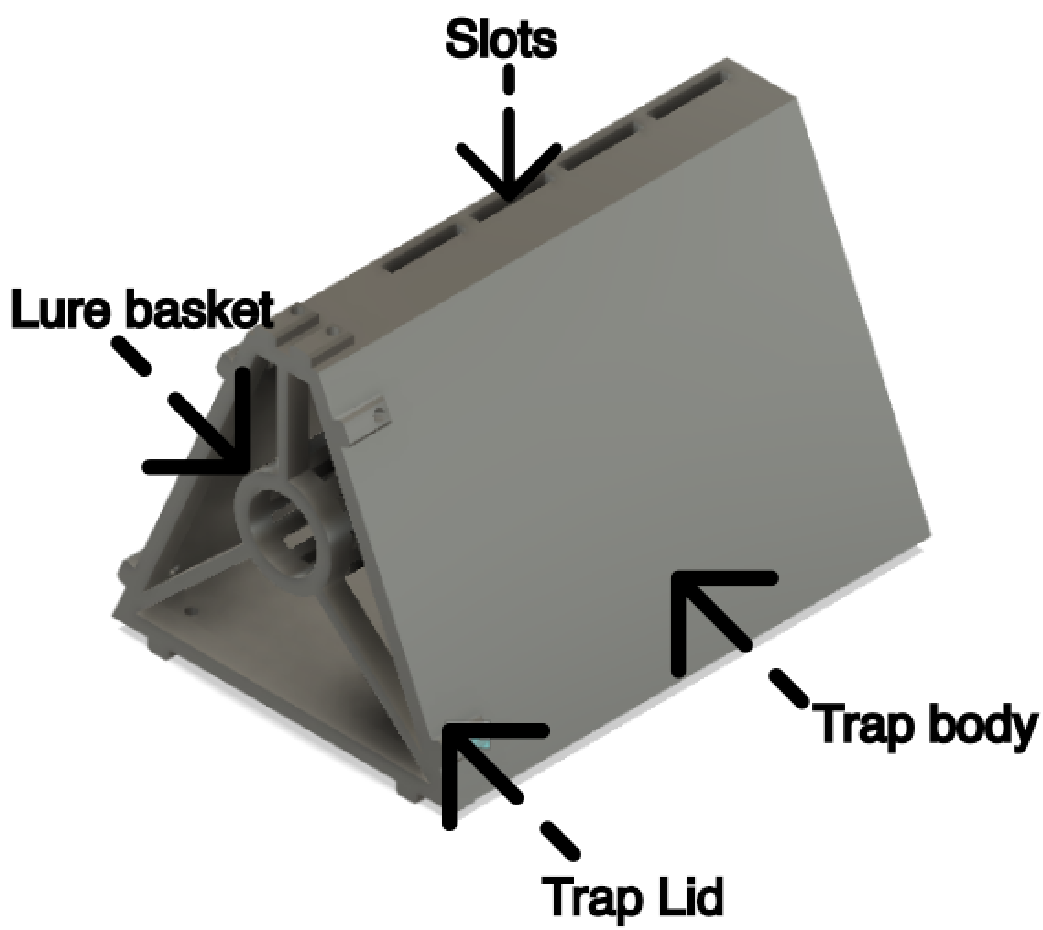


Figure 5.9: The CAD design with Fusion 360©of a trap integrating air quality sensors and slots with different lure locations.

This study employed two types of Metal Oxide (MOX) gas sensors, the SGP30 and ENS160 from ScioSense®, designed to detect a broad spectrum of Volatile Organic Compounds (VOCs) and equivalent Carbon Dioxide (eCO_2). Both sensors operate based on the principle that the resistance of the metal oxide layer changes in response to gas exposure. Notably, the ENS160 requires a warm-up period of up to 20 minutes and is suitable for high-power applications, whereas the SGP30, suitable for low-power, battery-operated devices, reaches stability after just three minutes. The ENS160 also features independent hot plate control, enhancing its selectivity and sensitivity by compensating for environmental factors such as humidity and ozone levels. In contrast, the SGP30 requires an external sensor to regulate temperature.

While various types of traps are available for capturing the Mediterranean fruit fly, for instance, the McPhail trap, our experiment exclusively utilized a modified Delta trap, also known as a Jackson trap (Figure 5.6). This choice was made to integrate the sensor hardware effectively and because it is a widely used trap design in the field for Mexico [38]. As depicted in Figure 5.9, the adapted trap design includes five slots at the top specifically for air quality sensor placement. These traps were constructed using a 3D printer and PLA—a biodegradable material—following the specifications from CAD models created in Fusion 360 software. The design retains the traditional dimensions of Delta traps but features a central basket. This addition is crucial as it stabilizes the lure's position within the trap, thereby minimizing variability in the sensor readings and ensuring consistent data collection.

Figure 5.9 illustrates the CAD model of the trap, designed using Fusion 360 software. This model retains the standard dimensions of a conventional Delta trap but incorporates five slots at the top specifically designed for mounting the air quality sensor. In practical field applications, the lure is housed within a plastic basket equipped with a hook, forming a soft grid to secure the lure. For our experiments, a similar basket was centrally placed within the trap to prevent lure movement and minimize measurement errors. This central placement does not impact the air flow or dispersion patterns within the trap, as confirmed by Lewis et al. [27].

The trap components were produced using a 3D printer, based on the CAD model. It consists of two main parts: the body and the lid, which were assembled using screws and nuts. The material used for printing was Polylactic Acid (PLA), a biodegradable polymer known for its low melting point, making it ideal for such applications.

The sensors within the trap are managed by an STM32F401 microcontroller board from St Semiconductors, featuring a 32-bit ARM Cortex-M4 core running at 84 MHz, with 512 KB of flash memory and 96 KB of RAM. Communication is facilitated via an I2C interface, programmed using STM32CubeIDE software in C language and utilizing the Hardware Abstraction Layer (HAL) library. This library supports the Arduino ecosystem, simplifying the development process by eliminating the need for additional programming.

5.2.3 Experimental Design

The experiment was designed to assess the sensors' capability to detect the presence of Trimedlure©, a widely used lure in Mediterranean fruit fly control strategies [38, 22]. Initial tests were carried out in a controlled environment—a clean room maintained at 25°C and 20% relative humidity—to establish the baseline noise levels for the sensors. In subsequent tests, the lure was strategically placed at varying distances (1 cm, 2 cm, and 3 cm) from the sensors within the basket of the trap (Figure 5.9). Although initial trials included adjusting the sensor's position along the trap slots, this approach proved ineffective and was discontinued in further tests.

Data collection focused on monitoring changes in CO_2 and VOC concentrations across varying distances during ten-minute intervals. Although additional time intervals were evaluated, the ten-minute duration was ultimately selected due to its efficiency in yielding results comparable to those from longer periods. This duration proved to be optimal for assessing each sensor's response to the chemical emissions from the lure under controlled environmental conditions. Detailed sensor responses, including variations in CO_2 and TVOC levels corresponding to different distances from the lure, are comprehensively presented in the Results section.

5.2.4 Sensor Performance Evaluation

The experimental results reveal distinct performance capabilities between the two tested sensors, the SGP30 and the ENS160, in detecting the presence of Trimedlure substance using measurements of equivalent Carbon Dioxide (eCO_2) and Total Volatile Organic Compounds (TVOC). The SGP30 sensor demonstrated limited effectiveness in eCO_2 detection, showing no significant change that could reliably indicate the presence of the lure. However, it could detect variations in TVOC levels, although the data were prone to noise and influenced by external factors such as ambient temperature and humidity.

Conversely, the ENS160 sensor exhibited robust detection capabilities for eCO_2

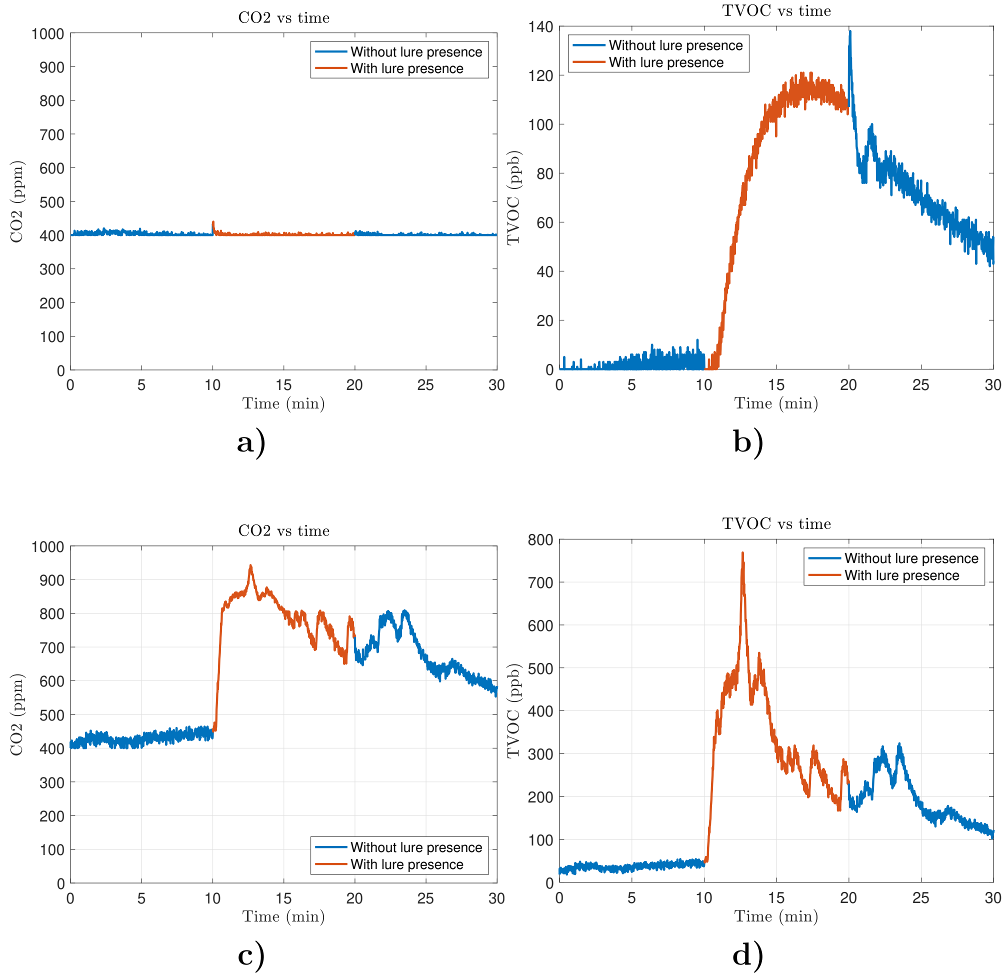


Figure 5.10: Resulting measures for the SGP30 (top) and the ENS160 (bottom) sensors in an experiment of 30 minutes: before setting the lure (min 1-10), with the lure set (min 11-20), and after removing the lure (min 21-30). The recorded data correspond to eCO_2 (a,c) and TVOC (b,d).

and TVOC, with less sensitivity to external disturbances. This sensor maintained consistent performance across various experimental conditions, and its readings significantly correlated with the known concentrations of lure substances. The detailed results are as follows:

- SGP30 Sensor Findings (Figure 5.10a-b):
  - eCO_2 Detection: The sensor failed to show any significant change in eCO_2 levels, remaining at baseline values around 500 ppm regardless of the lure presence.

  - TVOC Detection: The sensor responded to the lure presence with an increase in TVOC measurement, reaching up to 140 ppb. However, the response was unstable, fluctuating significantly with environmental changes.

- ENS160 Sensor Findings (Fig. 5.10c-d):
  - eCO_2 Detection: The ENS160 showed a clear response to the lure with eCO_2 levels increasing by an average of 200 ppm above the ambient baseline, providing a reliable indicator of lure presence.
  - TVOC Detection: This sensor detected TVOC concentrations consistently above the baseline, with an average increase of 300 ppb when exposed to the lure. The measurements were stable across multiple tests, with a low variance.

5.2.5 Distance-Based Sensor Performance

Further analysis focused on the effect of sensor distance from the lure on detection effectiveness. The optimal performance for the ENS160 sensor was observed at a 2 cm distance from the lure (Fig. 5.11a-b), where both eCO_2 and TVOC readings were maximized and most consistent.

- 1 cm distance: At this proximity, both sensors showed heightened sensitivity, but the ENS160 readings exhibited a tendency towards saturation, suggesting that too close a placement may lead to overestimation of lure concentrations (Fig. 5.11c-d).

- 2 cm distance: This distance was found to be optimal, offering a balance between sensitivity and accuracy, with clear differentiation between baseline and lure-present states (Fig. 5.11a-b).

- 3 cm distance: At this range, the effectiveness of the sensors decreased slightly, with lower but still detectable increases in both eCO_2 and TVOC levels compared to closer ranges (Fig. 5.10c-d).

These results underscore the ENS160's suitability for integration into smart trap designs, providing reliable, real-time monitoring of lure conditions that can significantly enhance pest management strategies.

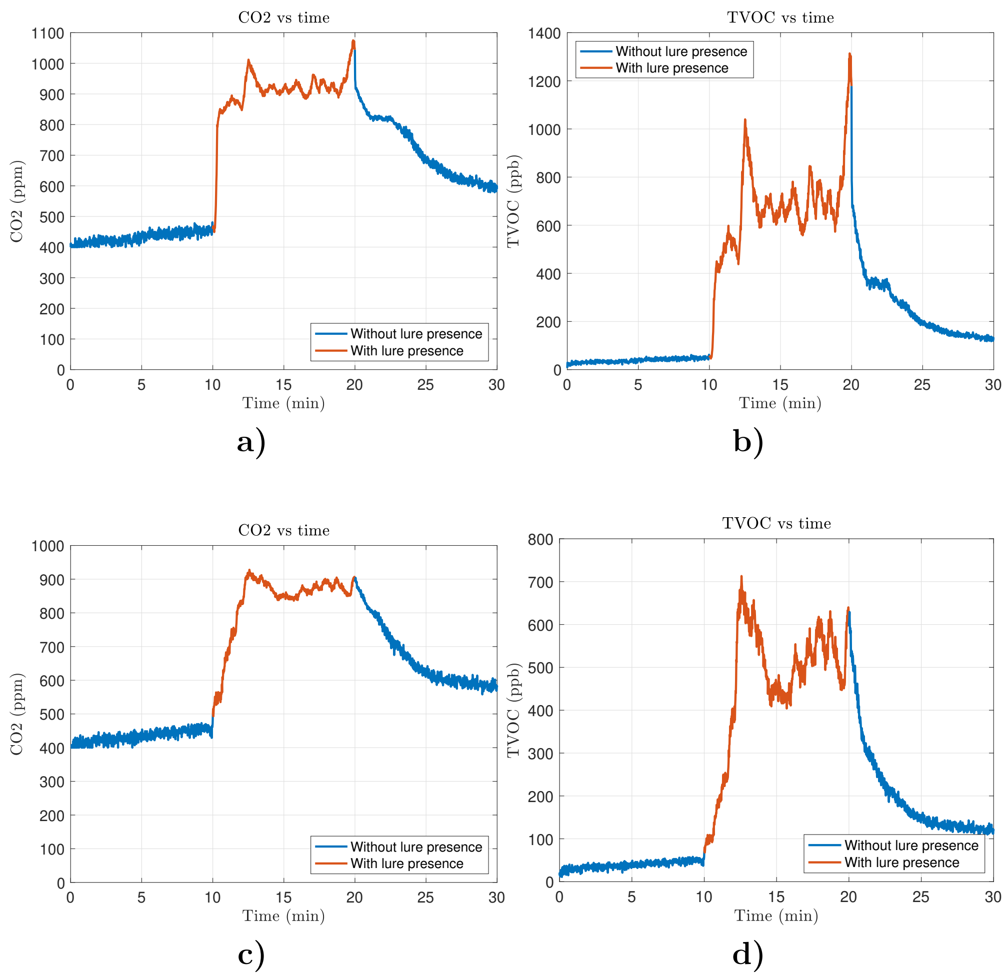


Figure 5.11: Results for ENS160 sensor when measuring eCO_2 and TVOC at (top) 2 cm and (bottom) 1 cm of distance between the sensor and the lure. Time intervals were distributed as in Fig. 5.10.

Chapter 6

Discussion

6.1 Comparison with traditional monitoring methods

In this research proposal, a *smart trap* design is presented, aimed at analyzing the acquired information on the Mediterranean fly pest. This design integrates camera sensors, radar (PCR), and other sensors to monitor the pest. The primary distinction between this proposal and traditional traps is that it not only counts specimens but also gathers additional information related to them through the complementary data provided by the proposed sensors. This work aims to demonstrate that the two-dimensional information from the camera, three-dimensional information from the radar, and other sensor data can be combined to intelligently determine the presence of the Mediterranean fly in a trap. Furthermore, it seeks to provide the necessary tools to prevent the establishment of the pest through a continuous monitoring mechanism based on automatic classification.

Without proper analysis of the information that a trap can capture, understanding the interactions between various factors and pest development is challenging. Moreover, food production can be significantly affected, and it has been shown that the cost of pest damage exceeds the cost of control [29]. Therefore, efficient monitoring with traps plays a crucial role in pest control, particularly for the Mediterranean fly. Currently, sensor-based *smart traps* can identify and count specimens as they enter the trap [60], but they have significant limitations: they require manual *in situ* reading, and the information they provide depends on their condition at the time of review. In this context, the need for more effective monitoring is evident [14], especially for the Mediterranean fly, which is the focus of this study. Developing an autonomous early warning system to detect the presence of pests is essential to reduce the likelihood of their spread and establishment [29].

Mexico has significant potential for agricultural development. However, this potential has been hindered by a lack of resources and economic support. Additionally, farmers often lack access to technological tools that would enable them to efficiently monitor and manage their crops. Moreover, the personnel involved in some monitoring projects do not possess the necessary tools for field operations. This motivates the research into the development of efficient traps.

The current limitations in pest trapping necessitate the proposal of an automatic monitoring system that combines data obtained from different sensors for analysis and monitoring. Two primary sensors, an RGB digital camera and a Pulsed Coherent Radar (PCR), are proposed for this purpose. The camera continuously monitors the trap, capturing the appearance of new specimens and providing two-dimensional information on color, texture, shape, among other attributes. The PCR sensor, on the other hand, uses presence information to monitor in real-time any species entering the trap, avoiding interference from light, dust, or noise that affects sensor-based traps. The two-dimensional tracking to locate position in image processing avoids unnecessary processing. The camera can analyze shape, color, or texture, providing information not only about the species but also about the current state of the trap. This allows experts to respond more quickly and take prompt action.

6.2 Advantages and limitations of the developed trap

By analyzing the information presented in Chapter 2, several commonalities can be observed: all traps are operated remotely, powered by solar cells or batteries, and report information to a central server. The processing unit is typically a microcontroller or microprocessor, and they connect to the server via interfaces such as GSM, GPRS, 3G, or WiFi. Their primary service is the detection of the Mediterranean fly, though not necessarily the specific species of the fly, and the information gathered must be validated by a specialist.

The main differences among the traps include the type of sensor used, the species they detect, their mechanical design, information processing capabilities, detection variables, and detection techniques. The sensors can be divided into two main types: those with cameras and those with sensors. Camera-based traps detect based on physical analysis of the image sensor variables, while sensor-based traps primarily detect based on attractants and do not distinguish the type of insect, merely counting them. However, there are exceptions such as in [43] and [44], where sensor signals are also used to acquire physical information from wing flapping.

Regarding species detection, the greatest risk of infestation for Mexico is from the *Ceratitis capitata* species, but other regions and crops report different primary species, such as *Bactrocera oleae* in Brazil. The mechanical design of the traps also varies depending on whether the objective is monitoring or capture, with classic designs (Jackson, Phase IV, McPhail) and custom designs. Custom designs, as shown in [14], need validation for effectiveness, as not all designs attract or disperse the attractant as efficiently as classic traps.

Information processing differs significantly based on the sensor type. Camera-based traps require a more complex system, such as a microprocessor, to process the information, enabling tasks like image processing and deploying artificial intelligence models ([51]). In contrast, sensor-based traps often use microcontrollers, which deliver basic information like measurements or signals for further processing ([29], [43]).

The detection variable also varies; camera-based systems use physical analysis of image sensor variables through various techniques ([29]) or artificial intelligence models ([24]). In contrast, most sensor-based traps focus on capturing the target species via an attractant and maintaining a count using an infrared sensor ([14], [29], [23], SnapTrap, RapidAIM) that does not discriminate insect type. Special cases, like those reported in [43] or [44], use wing flapping captured in optoelectronic or acoustic signals for classification, though these signals are vulnerable to ambient light or external sounds.

The development of the *smart delta trap* presented here demonstrates several advantages that significantly enhance the monitoring and control of the Mediterranean fruit fly.

One of the primary advantages of the developed trap is its integration of advanced sensor technologies, which allows for more accurate and real-time detection of the target pest. The use of Metal Oxide (MOX) gas sensors, such as the SGP30 and ENS160, provides precise measurements of volatile organic compounds

(VOCs) and equivalent carbon dioxide (eCO2) levels, indicating the presence of attractants within the trap. These sensors, managed by an SSTM32MP1, offer reliable performance with low power consumption, making them suitable for continuous field operations. The inclusion of a radar sensor operating at 60.5 GHz enhances the trap's ability to detect the presence of fruit flies through non-intrusive means, even under various weather conditions and low light levels.

Another significant advantage is the trap's design, which incorporates 3D-printed components made from biodegradable PLA material. This choice of material not only ensures environmental sustainability but also allows for precise customization and easy assembly of the trap. The structural design includes a central basket to stabilize the lure, minimizing variability in sensor readings and ensuring consistent data collection. The integration of WiFi capabilities facilitates real-time data transmission to central processing units or cloud-based storage, enabling remote monitoring and timely responses to pest detections. This connectivity significantly reduces the need for frequent physical inspections, thereby lowering operational costs and labor requirements.

Despite these advantages, the developed trap also faces several limitations. One of the main challenges is the high initial cost associated with the advanced sensors and radar systems integrated into the trap. While these components enhance the trap's functionality and accuracy, they also contribute to higher production and maintenance expenses compared to traditional trapping methods. Additionally, the complexity of the trap's design and the need for specialized knowledge to interpret the collected data can be barriers to widespread adoption, particularly among smallholder farmers.

Another limitation is the reliance on environmental conditions for optimal sensor performance. For instance, the air quality sensors require specific temperature and humidity levels to provide accurate readings, which may not always be present in field conditions for ENS160; however, the SGP30 sensor is more robust in this regard. Furthermore, the radar sensor, while effective in various weather conditions, may still face challenges in differentiating between target pests and other insects or objects within its detection range. This limitation necessitates additional validation by experts to ensure the accuracy of pest identification and to avoid false positives.

The deployment of the smart delta trap in remote or difficult-to-access areas poses another challenge. While the inclusion of WiFi capabilities allows for remote data transmission, ensuring consistent connectivity in such regions can be problematic. Additionally, the power management requirements for continuous operation of the sensors and communication modules necessitate robust and reliable power sources, such as solar cells or long-lasting batteries, which may add to the overall cost and maintenance efforts.

6.3 Potential improvements and future work

To address the limitations of the developed trap and further enhance its functionality, several potential improvements and future work directions can be considered. One possible improvement is the integration of additional sensors. In this regard, our results indicate that the inclusion of a time of flight (ToF) sensor could provide valuable distance measurements to substantiate the radar's detection data.

Although the radar sensor offers reliable detection capabilities, the main limitations is the lack resolution in the Z-axis. By incorporating a ToF sensor, the trap could provide more precise distance measurements, enabling better tracking of the target pests and reducing the likelihood of false positives. Additionally, the ToF sensor could enhance the trap's ability to differentiate between pests and other objects or insects within its detection range, thereby improving the overall accuracy of pest identification.

Another potential improvement is the development of an automated pest identification system based on machine learning algorithms. The first stage of the system was involved in the development of a basic classification model using neural networks to distinguish between the Mediterranean fruit fly and other insects. However, the model's performance could be further enhanced by incorporating additional features and training data to improve its accuracy and reliability. For this pourpose, the *AI app* was proposed in the architecture of the trap, which could be used to train the model with new data and update its classification capabilities over time.

The architecture proposed in this research could be further expanded to detect other pests and adapted to different traps or monitoring systems. For instance, the smart delta trap could be modified to target moth pests by incorporating additional sensors or attractants specific to these. With just a few modifications, the trap could be adapted to monitor moths.

The intention of the smart trap was mainly to be deployed in areas with WiFi coverage. However, the trap could be further improved by integrating additional communication modules, such as LoRa or Narrowband IoT (NB-IoT), to enable connectivity in remote or low-coverage regions. By expanding the trap's communication capabilities, it could be deployed in a wider range of environments, enhancing its applicability and reach.

Finally, the smart delta trap has the intention to be tested in field conditions to validate its effectiveness and reliability. This was not possible due to the COVID-19 pandemic and the time needed to validate the trap design. However, future work will focus on field testing to evaluate the trap's performance under real-world conditions and to gather feedback from end-users. This feedback will be crucial for refining the trap's design and functionality, ensuring its practicality and effectiveness in pest monitoring and control.

It is important to note that none of the designs presented in this research are published or patented. This will be the next step in the development of the smart delta trap. The design will be published in a scientific journal and patented to protect the intellectual property of the trap. In any way, the author ask for your discretion in the use of the information presented in this research.

Chapter 7

Conclusion

7.1 Summary of Findings

The research presented in this thesis aimed to design, develop, and validate a smart trap for monitoring the Mediterranean fruit fly (Ceratitis capitata). The smart trap integrates radar and camera sensors, leveraging advances in sensor technology, data processing, and connectivity to enhance pest detection and monitoring. The findings are categorized into several key areas: sensor performance, radar-based detection, system integration, and overall efficacy compared to traditional methods.

The radar-based detection system was a central focus of this study. The radar technology, particularly the W-band pulsed radar, was evaluated for its ability to detect and count fruit flies. Initial experiments with metal spheres validated the radar's detection zone and resolution. Subsequent tests with Mediterranean fruit flies demonstrated that live flies could be detected effectively, although dead flies posed detection challenges due to low moisture content and reflectivity. Experiments in dark conditions confirmed that radar detection improved significantly with live flies, indicating the importance of specific environmental controls for optimal performance.

One of the critical findings was the performance of different lenses (FZP and HBL) and their impact on detection accuracy. The FZP lens showed higher reflectivity and better performance under varying gain and HWAAS (High Way Application Specific) settings. However, the radar's ADC saturation at higher gain values necessitated careful calibration to avoid data loss. This meticulous calibration allowed for robust detection even under challenging conditions, affirming the radar's potential for entomological applications.

The integration of various sensors in the smart trap provided comprehensive data collection capabilities. The ENS160 sensor exhibited robust detection capabilities for eCO2 and TVOC, essential for monitoring environmental conditions that influence pest behavior. The sensor's optimal performance was observed at a 2 cm distance from the lure, where both eCO2 and TVOC readings were maximized and most consistent. This optimal distance ensures reliable, real-time monitoring of lure conditions, significantly enhancing pest management strategies.

Additionally, the trap's design considered various practical aspects, such as the mechanical stability provided by a polystyrene base and the strategic placement of sensors. The radar's capability to detect flies on a glue base further validated the trap's practical applicability in field conditions. The consistent detection patterns observed across different configurations underscored the system's reliability and adaptability.

Comparative analysis with traditional monitoring methods highlighted several advantages of the smart trap. Traditional methods, such as visual inspections and mechanical traps, are labor-intensive and less efficient in real-time data collection. The smart trap's integration with IoT and cloud services facilitated continuous, real-time monitoring and immediate data analysis. This connectivity allows for rapid response to pest infestations, reducing the reliance on manual inspections and enabling more proactive pest management.

However, the study also identified limitations and areas for improvement. The radar's sensitivity to environmental factors, such as ambient light and temperature, requires further refinement to ensure consistent performance across diverse field conditions. Additionally, the need for precise calibration of sensor parameters suggests that further development is necessary to create a more user-friendly and universally applicable system.

In conclusion, the developed smart trap demonstrated significant advancements in pest monitoring technology. By integrating radar and camera sensors, and leveraging IoT connectivity, the system offers a scalable, efficient, and accurate solution for monitoring the Mediterranean fruit fly. Future research should focus on refining sensor calibration, expanding the system's applicability to other pests, and enhancing user interfaces to facilitate broader adoption in agricultural practices.

7.2 Contributions to precision agriculture and integrated pest management

The contributions of the presented work to precision agriculture and integrated pest management (IPM) are significant and multifaceted. This research integrates modern sensing technologies, data analysis, and automated reporting systems to enhance the monitoring and control of the Mediterranean fruit fly, a major pest in fruit crops worldwide.

One of the primary contributions to precision agriculture is the development of smart traps equipped with advanced sensors and image processing capabilities. These smart traps autonomously identify and count pests, reducing the need for manual labor and enabling continuous, real-time monitoring of pest populations. By employing a combination of millimeter-wave radar and computer vision, the system achieves high accuracy in pest detection, even in challenging conditions where insects are constantly moving.

The integration of smart traps into precision agriculture frameworks allows for precise application of pest control measures. The detailed data collected from these traps, including the number and type of pests, helps farmers make informed decisions about when and where to apply pesticides. This targeted approach minimizes the use of chemical pesticides, reducing environmental impact and promoting sustainable farming practices. Additionally, the data-driven methodology supports better resource allocation, ensuring that water, fertilizers, and other inputs are used efficiently to maximize crop yields.

In the context of integrated pest management, the smart trap system offers several advantages. IPM relies on a combination of biological, cultural, physical, and chemical tools to manage pest populations in an environmentally and economically sustainable manner. The automated nature of the smart traps enhances the monitoring component of IPM by providing consistent and reliable data on pest behavior and population dynamics. This real-time data enables early detection of pest outbreaks, allowing for timely and targeted interventions that can prevent the spread of pests and reduce reliance on chemical controls.

Furthermore, the data collected by smart traps can be integrated into broader pest management systems, facilitating comprehensive monitoring and analysis. This integration supports the development of predictive models that help anticipate pest outbreaks and optimize control strategies. Machine learning algorithms and advanced data analytics can further enhance the accuracy and efficiency of these systems, providing valuable insights into pest trends and informing long-term pest management plans.

The work also addresses some of the challenges associated with implementing precision agriculture and IPM practices. The high cost of technology and the need for specialized knowledge to interpret data and implement strategies can be barriers to adoption. However, the research demonstrates that ongoing advancements in technology can help overcome these hurdles. By making these technologies more accessible and user-friendly, the research promotes wider adoption of precision agriculture and IPM practices, benefiting Mexico agriculture. This research significantly advances the fields of precision agriculture and integrated pest management by developing an innovative smart trap system.

This system enhances the accuracy and efficiency of pest monitoring, supports sustainable pest control practices, and provides valuable data for informed decision-making. The contributions of this work have the potential to improve crop health, reduce economic losses, and minimize environmental impact, ultimately leading to more sustainable and productive agricultural practices.

7.3 Future research directions

The future research and directions for the proposed work on the smart delta trap present significant opportunities for enhancing its functionality and applicability in integrated pest management (IPM) and precision agriculture. The current design and implementation of the smart trap, although robust, can be further refined to address some of its limitations and expand its scope. One potential direction is the integration of additional sensors, such as time of flight (ToF) sensors, which could provide valuable distance measurements to substantiate the radar's detection data. This would enhance the trap's ability to track pests more accurately and reduce the likelihood of false positives.

The incorporation of ToF sensors would also enable the differentiation between pests and other objects or insects within the detection range, thereby improving overall pest identification accuracy. Another avenue for future research is the development of an automated pest identification system based on advanced machine learning algorithms. While the initial stages of this research involved developing a basic classification model using neural networks, the model's performance could be further enhanced by incorporating additional features and training data. This improvement would increase the accuracy and reliability of the pest identification system, making it more effective in real-world applications.

Expanding the architecture proposed in this research to detect other pests and adapt to different traps or monitoring systems is another critical direction. For instance, the smart delta trap could be modified to target moth pests by incorporating specific sensors or attractants. This adaptability would broaden the trap's applicability, making it useful for monitoring a variety of pest species in different agricultural contexts. The trap could also be improved by integrating additional communication modules, such as LoRa or Narrowband IoT (NB-IoT), to enable connectivity in remote or low-coverage regions. This enhancement would allow the trap to be deployed in a wider range of environments, increasing its reach and effectiveness.

Field testing of the smart delta trap is essential to validate its performance and reliability under real-world conditions. Due to the COVID-19 pandemic, extensive field testing was not possible, but future work should focus on this aspect to gather feedback from end-users and refine the trap's design and functionality. Field testing will provide valuable insights into the trap's practical application, helping to identify any issues that may arise and addressing them accordingly.

The development and publication of the smart delta trap design in a scientific journal, along with obtaining a patent to protect its intellectual property, are crucial next steps. This will ensure that the innovations presented in this research are recognized and protected, fostering further development and collaboration in the field. Additionally, publishing the design will allow other researchers and practitioners to build on this work, contributing to the advancement of IPM and precision agriculture.

Future research should also explore the integration of renewable energy sources to power the smart delta trap, reducing its reliance on traditional power sources and making it more sustainable. Solar cells or long-lasting batteries could be used to ensure continuous operation, even in remote or difficult-to-access areas. This would enhance the trap's practicality and reduce maintenance efforts and costs.

The proposed future research and directions aim to address the current limitations of the smart delta trap while expanding its functionality and applicability. By integrating additional sensors, improving pest identification algorithms, adapting to different pests and environments, and conducting extensive field testing, the smart delta trap can become a more effective and versatile tool in IPM and precision agriculture. The publication and patenting of the design will further solidify its contribution to the field, promoting innovation and collaboration.

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