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Acoustic monitoring of airborne insects in outdoor environments

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Abstract

Insects are one of the most diverse groups of organisms and play a vital part in maintaining a balance in our environment. Over the decades, the insect population has been declining due to various factors such as pollution, biological degradation, and artificial lights. Artificial Lights at Night (ALAN) has had a significant impact on the insects. These insects are attracted to the light due to the vacuum cleaner effect. The presence of ALAN disrupts the path of insects and affect their behaviour which eventually kills the insects. The reduction in insect population would create an imbalance and a huge impact on the ecosystem. Thus, monitoring and identifying the insect species is important. In this thesis, we first analyse the technologies used to extract the properties of insects. Most of the state-of-the-art technologies in insect detection applications, either uses ALAN or the insect trapping method to attract the species. Therefore, in this thesis, we will use acoustic technology to detect and monitor airborne insects in outdoor environments. The sound technologies are non-intrusive, ubiquitous, cost-effective and do not require the use of light. We collected real-world audio and video data in three environments; urban, suburban and Artis Zoo experimental sites to detect and monitor the airborne insects. The sound data was manually annotated using the Audacity software and the ground truth. Then, we developed a lightweight insect detection algorithm to count the number of airborne insects from audio recordings. Furthermore, the performance of selected microphones in terms of range detection was evaluated to determine their feasibility in airborne insect detection. The microphones were able to detect sounds up to 1m in an outdoor environment. On average, the performance of airborne insect detection had a very good recall rate of 76%, 84% and 58% observed in urban, suburban and Artis Zoo experimental sites respectively. Whereas a low precision of 12%, 35% and 4.4% were observed in these distinct environments respectively. This is due to a large amount of noise present in the surroundings and the hard threshold used in the insect detection algorithm. The scope of improvement is later discussed in the future works section. Furthermore, insect classification procedures and the effect of various external parameters on the system were discussed and analysed.

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Acronyms

ABIS Automatic Bee Identification System

ALAN Artificial Lights at Night

ANN Artificial Neural Networks

CNN Convolutional Neural Network

DAISY Digital Automated Identification System

FFT Fast Fourier Transform

FMCW Frequency Modulated Continuous Wave

FoV Field of view

GMM Gauss mixture model

HIV Human Immunodeficiency Virus

HMM Hidden Markov Model

HSV Hue Saturation Value

IR Infrared Radiation

KNN k-Nearest Neighbors

LASER Light amplification by stimulated emission of radiation

LED Light Emitting Diode

LiDAR	Light Detection and Ranging
LOS	Line of Sight
MEMS	Micro-electrical mechanical systems
MKL	Multiple-Kernel Learning
mmWave	Millimeter Wave
NB	Naive Bayes
OCS	Optical Cross Section
PNN	Probabilistic Neural Network
RADAR	Radio Detection and Ranging
RCS	Radar Cross Section
RGB	Red Green Blue
RNN	Recurrent Neural Network
ROI	Region of Interest
SFPT	Stepped-Frequency Pulse-Train
SINA	Singing Insects of North America
SNR	Signal to Noise Ratio
SVM	Support Vector Machine
USDA	United States Department of Agriculture
VLR	Vertical-Looking Radar

Chapter 1

Introduction

The diversity of life on the planet is necessary for its continued existence, from single-celled organisms to animals with billions of cells. Earth is the home to an astounding variety of life forms. Biodiversity refers to the large variety of species found in a well-established environment, including plants, animals, and microorganisms. A healthy ecosystem is stable in its interactions between living organisms and non-living things. Biodiversity is an important component of our world that is accountable for a good environment. To begin with, it provides us with needs such as fuel, medicine, shelter, raw materials, and other natural resources that we need in our daily lives[2]. In addition, it is also responsible for the decomposition of substances which helps the soils and plants to have adequate nutrients, maintains the environmental cycles to have a stable ecosystem and plays a vital role in the regulation of climate[3]. More importantly, it also provides us with oxygen, food and water which are the basic requisites for the survival of all the life forms on Earth. These utilities are known as "ecological services", and they are given by biodiversity, without which the survival of humans and other living creatures is impossible. Despite adequate data sources and tools, the aim to quantify biodiversity remains a hurdle. There exist seldom answers to understand how biodiversity changes over space and time. To estimate biodiversity trends, every existing creature that makes up an ecosystem must be measured. As a result, it is critical to track the evolving risks to biodiversity throughout time.

Over the last few decades, there has been a significant challenge to biodiversity, which has resulted in changes and numerous disruptions to the ecosystems caused by humans and their activities. The acquisition of forests for the raw materials required for human beings had a significant impact on biodiversity and ecosystems. It leads to deforestation and causes species extinction. Forest destruction reduces biodiversity by creating an unnatural habitat for many species. The pollution caused by the activities of humans leads to climate change. Climate change and its consequences may be the primary direct factor of biodiversity loss and changes in ecosystem services[2][4]. The introduction of exotic species to an existing ecosystem is also a form of threat in terms of existing resources and predation. Exotic species can change the existing ecosystem and cause harm to the existing species in the ecosystem. Overexploitation is also an important threat to biodiversity[4]. Human activities such as overfishing, overharvesting fall under overexploitation. Furthermore, the extinction of certain organisms, such as insects, birds, and animals, has also posed a serious threat to biodiversity. Humans disrupt the ecosystem's balance, whether intentionally or unintentionally. Though nature can replenish itself, it is not enough at the rate at which we the people are declining it. It is the most valuable asset that a human has ever got and it is our responsibility to save the ecosystem. Hence we must preserve them to have a safe environment for our future generations.

1.1 Motivation

Insects are one of the most important and diverse groups of organisms[5]. Over half of the estimated 1.5 million species belong to the class of insects but merely 10% of it has been identified till now[6]. Insects are also biological creatures that contribute to the preservation of the ecosystem, as insect habitat is one of the most crucial components for ecological management[6]. Insects provide many ecosystem services. Insects are responsible for ensuring the ecological foundation for terrestrial habitats[7]. They help us to pollinate the flowering plants, which account for one-third of all food produced in the world[8]. The decomposition of organic wastes provides the soil with a wealth of nutrients that are valuable in agriculture as well as for plants to fulfil certain functions including photosynthesis. Insects also keep pests in control which minimises the loss of crops in the agricultural field[9]. Insects also have common medical values that are used in some parts of the globe to treat a variety of illnesses, including bacterial infections and chronic diseases such as cancer, Human Immunodeficiency Virus (HIV), and much more[10].

Most of the insect species have survived massive extinctions in the past and has been an integral part of the ecosystem for more than 400 million years[11]. Regrettably, just like other animals and plants, some insect species are declining rapidly and are becoming endangered[11]. This decline is observed due to the increased threats to insect populations. This includes industrialisation, climate changes, artificial lights and much more. Artificial lights have caused a significant threat to the insect population over the last few decades[12]. ALAN is known to have significant effects on insects; it is widespread and has been rising at a pace of 2-6% per year over the previous decades worldwide, causing enormous changes in natural light regimes and endangering biodiversity[12]. ALAN tends to attract various insects based on the 'vacuum cleaner effect' from distant locations. These lights have a tremendous influence on insects at night because nocturnal insects are extremely sensitive to the spectrum of wavelengths[13]. This, in turn, has an impact on their migratory, physical, and biological behaviours. All these factors dwindle the insect population and create an imbalance in the ecosystem. Several global projects aim to conserve endangered animals such as 'Save Rhinos', 'Save Tigers', but there are relatively few projects that aim to conserve insects which also forms a crucial part of the biosphere. Also, the extinction of certain insect species may affect the life cycle of all living creatures, reducing biodiversity. It would create an imbalance that leads to a huge impact on the ecosystem. As insects are a significant species that constitute the ecosystem, monitoring and identifying them is considered important. Moreover, insect preservation is considered especially critical in the light of global climate change and the ongoing degradation of ecological systems.

1.2 Problem statement

Numerous research is carried out in insect detection and monitoring applications. The current research is mostly carried out in indoor environments or in specified and closed environments. There are minimal consequences for insect detection and monitoring in outdoor areas. Some of these applications include catching insect pests in agricultural fields and trapping common houseflies using artificial lights. These artificial lights in turn affect the migratory behaviour of insects and eventually kill them. Moreover, the existing technologies are highly complex in terms of cost and design setup. Thus, this research will focus on a cost-efficient and flexible system that will be used in insect monitoring applications in outdoor environments without using artificial lights.

1.3 Challenges

In this section, we will discuss the challenges involved in monitoring and detecting insects in outdoor environments. At first, there will be not adequate resources such as power readily available, which limits us to determining the type of technology used in this research. The design of the system setup plays a major role in deploying them in the field. There will be an ample amount of static and dynamic noise in the surroundings because of external factors such as human interaction, machinery noise, vehicular noise, environmental noise and much more. In addition to this, the movement and locomotion of the wild insects are not controlled by us, so the appearance of these insects near the sensor becomes more challenging when there are multiple insects present near the sensors.

1.4 Research questions

The main research question is 'How do we monitor and detect the airborne insects in outdoor environments without using light?'. The sub-questions that will be answered in this research are:

- What is the suitable sensor technology to detect and identify the airborne insects in urban and suburban outdoor environments?
- What is the feasibility of this technology in insect monitoring applications?
- What is the performance of the suitable sensor technology?
- What are the ways to identify the airborne insects using the suitable technology?

1.5 Approach

This research will begin with the relevant literature in monitoring the airborne insects using various technologies such as image, sound, optoelectronics, RADAR and LiDAR. This study will also help us understand how each technology can be used to determine the properties of insects. As we discussed earlier, the motive of our research is to monitor and detect insects without the use of artificial lights. Some technologies do require these artificial light sources to capture insects. Moreover, the previous research also involves harming the insects by trapping them or long exposure to electromagnetic waves. It will also result in a decrease in the insect population because these practices eventually kill the insect species. Thus, considering the previous research and ongoing challenges, it was decided that acoustic sensors will be used to obtain the airborne insects' data in outdoor environments. A comparison of a wide range of microphone types was carried out to ensure that the appropriate microphone could be used for detecting airborne insects. Later, a maximum range detection was performed on selected microphones to measure their feasibility in insect monitoring and detection applications. Next, we will use the performance metrics to determine the performance of the system in insect detection and monitoring in three different environments. Finally, we will discuss how the recorded data can be used to classify the insects.

1.6 Organization of the report

In this section, we will address the structure of the thesis report. Chapter 2 provides the relevant background in entomology and the technologies for entomological research. It will help the reader to have a better understanding of this field of study. Chapter 3 deals in the literature review on insect monitoring and detection applications. By the end of this chapter, we will have discussed and motivated the reasons for employing acoustic sensors to detect airborne insects in outdoor environments. The types of microphones used in the experiments will be discussed in Section 4.2. Later in this chapter, we will discuss the hardware setup (Section 4.3), insect detection algorithm (Section 4.4) and performance metrics (Section 4.5) that will be used for this research. The next, Chapter 5 will discuss the data collection and the annotation process. The environmental conditions observed during the experiment will be discussed in Section 5.2. The collected data in various environments, analyzing the insect data, and the performance of three different microphones used in this research will be discussed in detail in Chapter 6. Finally, in Chapter 7, the summary of the thesis will be discussed along with the future scope of this research.

Chapter 2

Background

In this chapter, we first discuss the insects and their relevant background. Later, the technical aspects involved in insect identification and their functioning principles are discussed.

2.1 Entomological background

Insects are a type of animal that are thought to have existed millions of years ago, even before dinosaurs. Fig. 2.1 represents a taxonomical chart that is used to categorise the biological organisms based on their characteristics. In the taxonomy chart, insects belong to the Animalia kingdom as they are multi-cellular organisms. Insects are invertebrates, which means they lack a backbone and instead rely on an exoskeleton for their body support and structure. They also contain segments in their bodies and a jointed pair of appendages, which places them in the phylum Arthropods. Insects, spiders, scorpions, millipedes, crabs, and many other species belong to this phylum. Insects are generally six-legged, which distinguishes them from other Arthropods and places them in the Insecta class. The insects are grouped in the class level. To identify the family it belongs to, we will have to look into the characteristics of insects.

An insect body usually consists of three sub-parts namely head, thorax and abdomen. The head is the anterior part of the insect and contains a pair of antennae, a mouth, and eyes. This part is for sensory input and food consumption. Thorax is the intermediate part of the insect separated into three segments and accounts for insect movements. It consists of a pair of legs in each segment of the thorax. Additionally, the wings of flying insects can be observed in this area. The abdomen

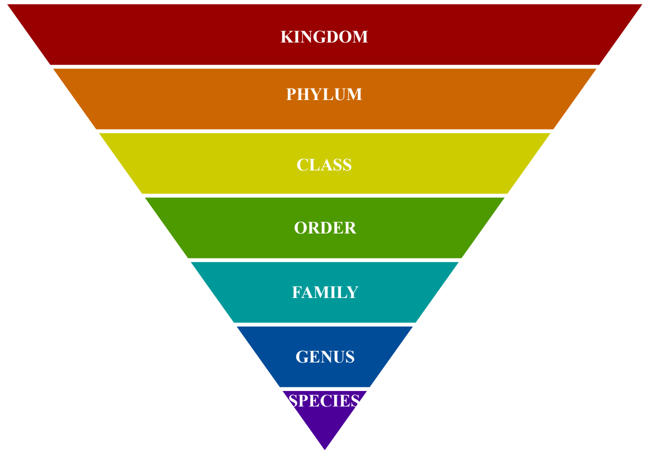


Figure 2.1: Taxonomy chart

is the rearmost part of the insect. It comprises internal anatomies (digestive system, excretory system, respiratory system, and reproductive system). These are the most important characteristics of insects that can help us categorize them.

Winged insects belong to the Pterygota subclass, whereas wingless insects belong to the Apterygota subclass. Order is the next level in taxonomic classification. There are up to 30 orders of insects, with many species grouped. Only four insect orders have no wings, while the remaining 26 are split into Endopterygota and Exopterygota. Although this newest distinction among flying insects does not allow us to differentiate insects using technology, it is considered an entomological division of insect identification. To identify the species of insects, we must have more knowledge about insects' properties. This includes the type of antenna, body shape, body mass, colour, wing type, wing size, wingbeat frequency, wingbeat sound, and the other sounds emitted by insects.

An insect tends to emit a sound that is to alert or inform insects for various purposes[14]. This includes songs for gathering in a colony, courtship and reproduction. They also can produce 'squawk' sounds. This auditory response alert other insects to a potential threat. There are five different ways insects produce sound:

- Stridulation is heard as a chirping sound which is generated due to the friction generated by two body parts.
- Percussion is heard as tapping or a drumming sound which is a result due to

the striking of body parts against a hearing substrate.

- Vibration is heard as a buzzing or humming sound which is produced by the oscillation of wings in the air.
- Tymbal Mechanism is heard as clicking sound produced through the contraction of vibrating drum membranes known as tymbal muscles.
- Air expulsion is heard as whistles which are due to the ejection of air or fluid through a body constriction.

2.2 Insect classification pipeline

In this section, we will take a look at some of the technologies that can be used to monitor and identify insects based on their properties. There are a few stages involved in the classification of insects which is shown using functional blocks in Fig. 2.2. It consists of three blocks namely data acquisition, data processing and extraction, and classification.

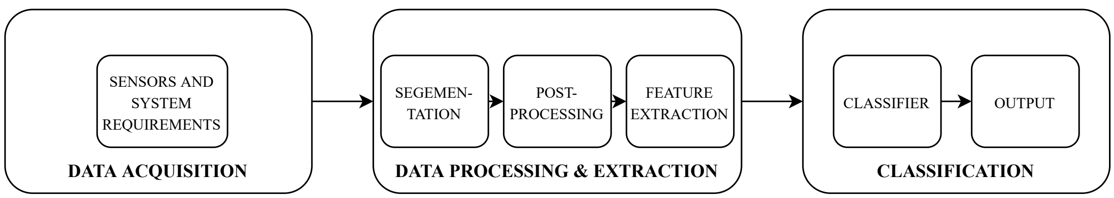


Figure 2.2: Insect classification pipeline

- **Data acquisition:** This stage involves collecting the insect data from heterogeneous sensors such as cameras, microphones, digital recorders, optoelectronic sensors, RADAR, and LiDAR. After the data is collected from the sensors, it is either stored in a memory device which is usually attached to the system or sent to the desired system for further processing. In this stage, this thesis will focus on detecting airborne insects in outdoor environments without using artificial lights.
- **Data processing and extraction:** This stage involves taking the raw data and turning it into informative values that can be used to detect and classify insects based on their characteristics. Raw data is primary data obtained from the sensor without a loss in quality or alteration. This stage is subdivided into three steps which are as follows:

- **Segmentation** is the process of dividing large data into small constituent regions. It is done to reduce the computational complexity of the system. Later, in this stage, the noise in the system is removed from the input data which is done by applying a filter. This enables us to clearly visualise the data that is required for our purpose and ultimately increases the overall accuracy in identification.
- **Post-processing** is the process to determine the presence of insects in the recorded data. In this thesis, we will develop a lightweight insect detection algorithm to determine the occurrences of insects.
- **Feature extraction** is the process of extracting the properties of insects using an algorithm. The algorithm reduces the need for human intervention and can easily extract the features automatically. The features of insects are not limited to include their colour, shape, size, and wingbeat frequency. In this stage, the wingbeat frequency and the pattern of the insect wingbeat are determined. This removes the unwanted data and turns the massive data into the set of essential data for subsequent learning and interpretation of insects, considerably reducing the computational complexity of the system.

• **Classification:** This is the end stage in the insect classification pipeline which is used to classify the insect species using a classifier to determine the output result. A classifier is used to recognise the insect species based on the extracted features of insects. This step particularly involves advanced machine learning algorithms. Some examples used in insect classification applications but not limited to include Artificial Neural Networks (ANN), Convolutional Neural Network (CNN), Hidden Markov Model (HMM), Gauss mixture model (GMM), k-Nearest Neighbors (KNN), Naive Bayes (NB),Probabilistic Neural Network (PNN), Recurrent Neural Network (RNN), Support Vector Machine (SVM), and Random Trees[15][16][17][18]. The extracted data is given as an input to one of the classifiers. Some of the data are utilized to train the model. This informs the model about the outcome that it will create. The gathered data is then given as an input to the model, and we get the outcome of insect classification based on the training sets.

2.3 Identification technologies

In this section, we will take a look at some of the technologies that can be used to monitor and identify the airborne insects.

2.3.1 Image recognition technology

The identification of insects using images captured by a camera is the most widely used method in research because it is the foundation that allows us to distinguish insects based on visual characteristics such as colour, shape, size, and the type or pattern of their body parts. Although this technology to classify insects looks like a trivial solution, it is also considered a tedious method.

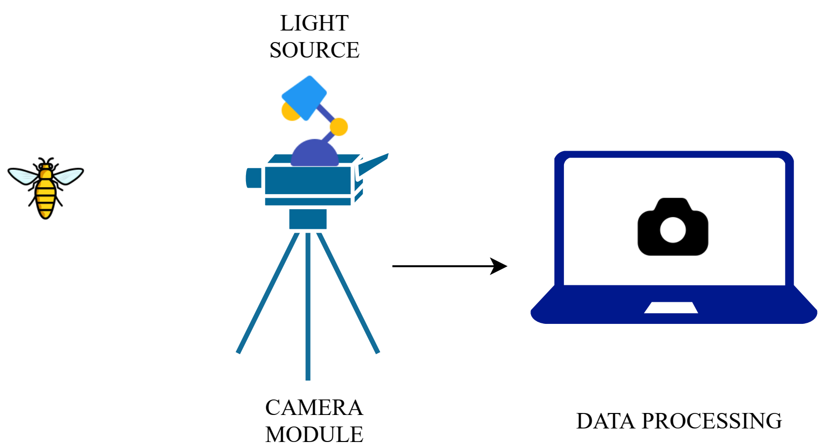


Figure 2.3: Functional diagram of image recognition technology

Fig. 2.3 shows a functional representation to detect the insects using image recognition technology. A light source is attached to the sensor system to capture the insects when there is no or minimal natural light. These collected images and first made to separate from the background. The tiny objects that reflect noise are also scrapped out in this process. Usually, all the images are in the form of Red Green Blue (RGB) colourspace. Similarly, the filtered image is also in the form of RGB colourspace and is converted into Hue Saturation Value (HSV) colourspace. The colourspace transformation aims to enhance the abstraction of an image and thus increases the accuracy of identification[19]. The images are then divided into smaller sections to compute a rectangular segment of the insect. One such process allows us to separate insects from one another. Subsequently, a contour of the insect image is selected to idealise the shape of the object and avoid overlaps. The processed image is then used to extract the morphological features of insects and given as an input to the classifier model. These classifier models compute the data sets and categorise the insects.

2.3.2 Sound recognition technology

This method captures the sound of the insects during their basic activities such as eating, mating, moving, chirping and singing.

Figure 2.4: Functional diagram of sound recognition technology

A microphone or a digital recorder is used to record the sounds of insects. Fig. 2.4 shows a functional representation to detect the insects using sound recognition technology. This model is said to have a multi-directional capability to record sounds based on the type of microphones used. Pre-processing involves identifying the sound activity region of insects. This comprises choosing a sampling frequency, splitting the signal into smaller frames, and smoothing the signal with a window function. The parameterization focuses on computing the descriptors that account for valuable information of the signal. This step ultimately reduces the background noises that were recorded by the microphone. The classification stage involves comparing the unlabelled input feature with established statistical models of target classes. The degree of proximity between the input and the models is used to make a decision on the identification.

2.3.3 Optoelectronic technology

This technology is based on the wing characteristics of insects. The system design is a sensor network that consists of an optical device coupled with an electronic system. Optical technology includes light sources such as Light amplification by stimulated emission of radiation (LASER) and Infrared Radiation (IR) Light Emitting Diode (LED), which acts as an emitter. The electronic system is considered as the array of phototransistors that acts as a receiver. The light source emits the light which is received upon the phototransistor. Whenever the winged insects come in contact in between the emitter and receiver, partial occlusion of the light occurs due to the fluttering of wings. This obstruction of insects creates an electrical fluctuation detected by a change in current in the photodiode. This signal output from the electronic board is given as input to the digital sound recording system. This sound wave is filtered and converted to a form in order to identify the wingbeat frequency of the flying insects. A functional representation of this technology to detect airborne insects is as shown in Fig. 2.5.

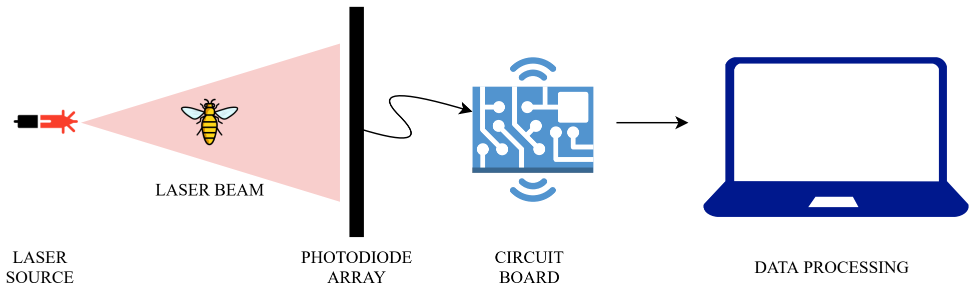


Figure 2.5: Functional diagram of Optoelectronic technology

2.3.4 RADAR technology

Radar is an abbreviation for RADAR. The radar consists of a transmitter and receiver. This is to generate electromagnetic waves and retrieve the attributes of the object respectively. When the waves hit the object, the signal is scattered back in all possible directions. Some of these backscattered signals with some amount of energy are collected by the radar. The change in phase between the transmitted and received pulse is measured. It provides us with an insight into the speed and the direction of the object on the radar. From the radar, we will also be able to extract the Radar Cross Section (RCS) value. This RCS value is an important parameter considered for the classification of insects. This will help us to extract some morphological features of insects such as the shape, size and body mass. Along with it, we will also be able to detect the wingbeat frequencies of the insect. These parameters help us to classify the insect species based on this technology. In radar, there are multiple types such as entomological radar, pulse-based radar, dual polarization radar, vertical looking radar, and doppler based radar systems. Each of these radars has it is working but the principle of detecting targets is performed using transmitted and receiving signal. A functional representation of this entomological to detect airborne insects is as shown in Fig. 2.6.

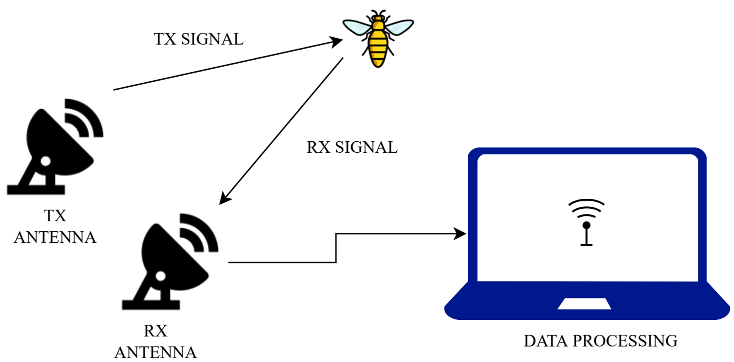


Figure 2.6: Functional diagram of Entomological RADAR

2.3.5 LiDAR technology

LiDAR is an abbreviation for LiDAR. This technique operates in the optical region of the electromagnetic spectrum, utilizing light waves to extract object characteristics. The system uses a LASER light (acts as a transmitter) to transmit the light waves and a photodiode (acts as a receiver) that receives the backscattered radiation. The source sends rapid pulses and determines the time it takes to reach back to determine the distance (time of flight) and the 3D map of the object. Like radar, from lidar, we can obtain Optical Cross Section (OCS) value which is a primary parameter to detect the wingbeat frequency of an insect. A functional representation of this technology to detect airborne insects is as shown in Fig. 2.7.

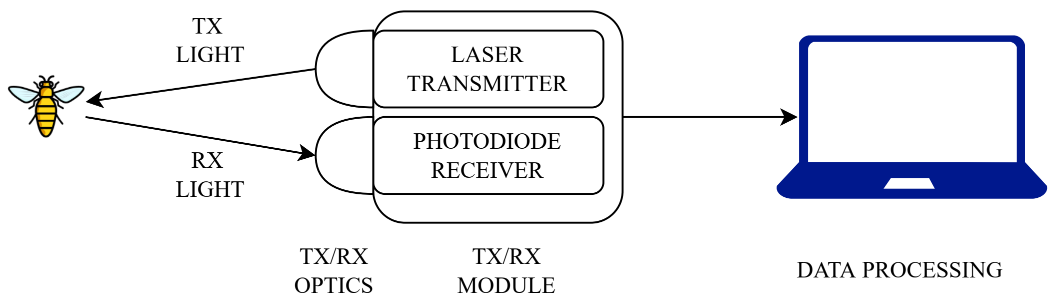


Figure 2.7: Functional diagram of LiDAR technology

2.3.6 X-ray technology

An X-ray, also known as X-radiation which uses high electromagnetic radiation that penetrates the body. One of the most popular applications is in healthcare systems[20]. It is used in hospitals by professionals to scan and monitor the conditions of our bodies in order to detect the presence of any disease. Another application of X-ray is predominantly used in airports for scanning our body and luggage. This would help to circumvent the presence of any dangerous goods carried inside the aircraft.

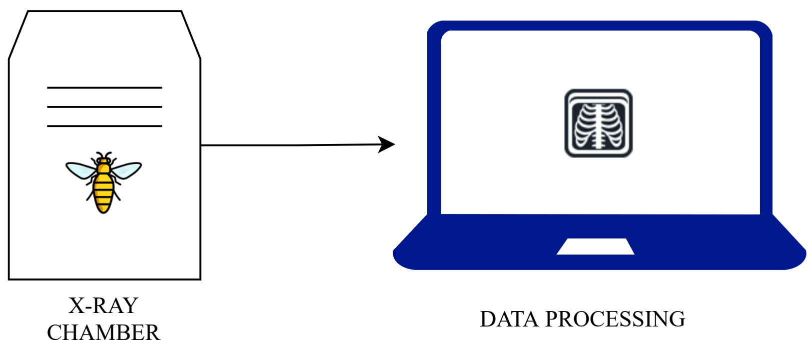


Figure 2.8: Functional diagram of X-ray technology

Similarly, this method can also be considered to classify the type of insects. When the insects pass through the chamber of X-ray, the outline shape and size would help us to determine the type of insect. This method would help us through the insect body past their exoskeleton and uncover the soft tissues or the softness of the insect. This would be an additional property to classify the insects. The contrast of the image improves when the wavelength is longer. Likewise, the image is brighter and stronger whenever the beam intensity is high. However, when the intensity is strong and the wavelength is long, it becomes more harmful for the insect. Thus this technique may affect the insect psychologically and eventually kill them. This is against the goal of our research as this method would decline the insect population.

2.4 Analysis

In this section, we will discuss the overview of these technologies using different parameters as shown in Table 2.1. This table has been developed with a conventional outdoor environment conditions. It is because each technology will have its own drawbacks in extreme environmental conditions. For example, the camera technology might not be suitable in foggy conditions unlike other sensors whereas the sound and radar are prone to windy conditions due to its noise and ground clutters respectively. Considering the parameters from technological comparison, we will further perform the literature review in insect detection and monitoring applications.

Parameters/ Technology	**Image**	**Sound**	**Opto-electronic**	**RADAR**	**LiDAR**	**X-ray**
Accuracy	Moderate	Moderate	High	Moderate	High	Moderate
Range	Low	Moderate	Low	High	High	Low
Sensitivity	Moderate	High	Low	Moderate	Low	High
Complexity	Moderate	High	Moderate	Moderate	Moderate	Moderate
Costs	Moderate	Low	Low	Moderate	High	High

Table 2.1: Technological comparison

Chapter 3

State-of-the-art

3.1 Literature review

In this section we will discuss how different technologies have been used to categorise the insect species.

3.1.1 Image technology

Automatic Bee Identification System (ABIS)[21] is a research project that provides the identification of bees by analysis of wings of the insects. A background illumination on the wings of insects is done to analyse the veins and transparent skin of insect image and are placed under a microscope. The veins and the cells of the wings are closely analysed from which numerical feature vectors are generated to identify the bee species. This led to features of insect wings such as area, circumference, veins length, skins length, etc can be determined by this system. This system to identify the bees in all the levels of the taxonomical chart was considered successful with an accuracy of 99.3%.

Yang et al.[22] proposed a method to identify the insects based on computer vision technology. The authors have extracted 14 edge features of an insect to recognise the insects. The edge features of the insects are the outline physical characteristics of the insects. Some of the edge features that are not limited include a spherical shape, rectangularity (ratio of insect area and product of their height and breadth size), and eccentricity. The edge features are extracted using the contours of the insects. Random Trees machine algorithm was used to obtain the output based on the feature extraction method. The system was developed with GCC and OpenCV libraries. The methodology was tested on 7 species of insects, each containing more than 20 samples. Since the number of samples is quite low, the accuracy of 6 different species proved to have 100% but the average recognition accuracy of all 7 species dropped to 97%.

Le-Qing and Zhen.[19] used the colour parameter and the SVM classifier for this purpose. The specimen of Lepidoptera insects were captured through the digital camera. The specimen consisted of 10 species with an average of 47 to 69 samples of each species. After segmenting the image from the background, the two wings of the image is cut out and their orientation is calibrated. The feature of the image is extracted through RGB channels. This is accomplished by recomposing the calibrated colour wing image into three single-channel images, each of which is represented by a grey-scale image. Each of these channels, the region of wings were divided into 40 blocks and as feature data for each block, the mean value and standard deviation are calculated. Thus 480-dimensional feature was used to extract from both the wings and fed as input to the classifier. This method tends to have an identification rate of 90% on average.

Wang et al.[23] developed a system that automatically classifies the insect images on the order level in the taxonomy chart. The authors start with the importance of classifying an insect up to the order level. They take the samples of 9 different orders of insects and apply ANN and SVM to identify them. The six body shape features of insects such as body area ratio, eccentricity, width and length ratio, and colour complexity are computed. These features form a base for insect identification with the machine learning algorithms. The ANN classifier outperformed the SVM with good stability and accuracy of 93%.

There were only a few examples in which the field-based setup of insect classification took place. Faithpraise et al.[24] developed a pest recognition using a k-means clustering algorithm. This algorithm was especially used to segregate the pest from the plant images that were captured. Through the training datasets, the pests were rotated by 5 degrees in each rotation until 360 degrees. This was done to set the tuning threshold to identify the pests more accurately. This recognition system was tested on the input images and showed promising results. Mayo and Watson[25] developed a system for the identification of live moths. The second author collected the images through Digital Automated Identification System (DAISY) over one calendar year. ImageJ toolkit was used to extract the features of these species. The global colour features are measured and are extracted and converted into patches. The mean pixel values are determined. Xie et al.[26] used advanced multiple task sparse representation and Multiple-Kernel Learning (MKL) techniques to construct an insect detection system. This system was mainly developed to improve recognition performance by combining numerous properties of insect species. The data of 24 different species of insects from common crop fields were collected through a Nikon camera. The raw features such as colour, texture, and shape were used to extract using the sparse coding technique to find the insect species. Later, this technique was compared to the general machine algorithms present. For compatibility, the authors also collected the data of 20 butterfly samples and 221 insect species datasets were collected from Wang and lab-based datasets. This method showed an accuracy rate of 97% and 90% on respective datasets and proved to be much more superior than other techniques.

Kasinathan et al.[15] applied modern machine learning techniques on 24 insect classes of Wang and Xie's data set to classify insects. They applied the algorithm on foreground extraction and contour identification to identify the insects as well as to improve the computational complexity and classification accuracy compared to previous works. The training set included 70% of the images from the data set. Image augmentation of the data was performed to increase the classification accuracy and eliminate the complication of training sets. The nine shape features of an insect was obtained and fed into classifiers such as ANN, SVM, NB, KNN. An erratic result was observed in other algorithms and hence they proposed a CNN classifier to improve the accuracy. Even with all of the classes from both datasets present, the proposed CNN classifier had a far higher accuracy rate of 90%.

In recent years, Diopsis, a research organisation who have developed an automated and computerised electronic system that is used to classify and monitor insects. They have installed a camera that snaps every 10 seconds round the clock, save it and send it to the server through wireless technology. They then count the number of insects and classify the insects with deep learning techniques. Finally, they determine the biomass of the insects to increase the accuracy of classification. They have installed up to 80 cameras in the Netherlands and have closely classified approximately 19500 insects.

3.1.2 Sound technology

Potamatis et al.[17] and Ganchev et al.[14] worked for the progress in the development of singing insects identification. The test was performed on a pool of 220 and 313 insect species respectively. They evaluate the performance of singing insect species such as crickets, katydids and cicadas. These insects are well known for generating sounds through stridulation and tymbal mechanisms. The sound database was gathered from the Singing Insects of North America (SINA) and Insect sound world. The authors have compared three different classifier models PNN, GMM and HMM to identify the insect species and determine their results. On species level of identification, PNN and GMM show a better result with an accuracy of 86% while HMM had a lower performance while compared to the other two models with an accuracy of 75%. However, the fusion of PNN and GMM had an accuracy of 90% on 220 insect species. But, when the classification in the order of family/subfamily and genus is taken into account, GMM is considered to outweigh the other two classifiers with a recognition rate of 98%.

Le-Qing[27] also derived a method to identify insects sounds from features such as insect movement, stridulation and feeding. The insects present in stored grain products, leaves and soil were considered for this experiment. The author had obtained the acoustic data from the insect sound library established by Richard Mankin's research team from the Agricultural Research Service (ARS) of the United States department of agriculture (USDA). Later, the insect sound features were extracted with MFCC and for classification, the PNN model was used. This PNN based classification addresses the problem of Bayesian classifiers. This approach was performed on a computer application software Matlab with 50 different acoustic sounds of insects. The time it takes to identify a species is around 10 seconds with an identification accuracy of 96%.

In[28],[29], the concept behind the identification of insects was using bioacoustic signals. Where [28], involved spectral and temporal features and involved SVM. [29] involved in collecting the digital sounds of insects from Insectsingers of 88 different species. The sound files were tested on MFCC and LFCC to compare the efficacy and SVM algorithm was used as a classifier. The LFCC had achieved a 99% which is a per cent higher than that of MFCC. In [28] five species of cicadas were for recognition using the spectral and temporal features. These Iranian cicadas were recorded in a ZOOM-H4 audio portable recorder. Finite impulse response Chebyshev filter was used to remove the lower frequencies that fall below 2.5kHz. As the insect sound ranged between 2-13 kHz, the ambient sounds below the threshold were neglected.

The generic algorithm has used a classifier and this observed an accuracy of 97.76% when all the features were taken into consideration.

Noda et al.[30] developed a sound parameterization technology that used a combination of MFCC and LFCC algorithms to identify insect species. They gathered data for 343 species of crickets, katydids, and cicadas from the SINA and Insectsingers libraries. The authors have performed pre-processing method from the datasets so that the feature extractor could provide meaningful information for identification. Later, for segmentation, they have made such a way to extract calls produced by the particular species. By this technique, the data is split into individual samples and stored whenever the pattern is identified. There were two classifiers SVM and random trees used for the comparison to check which yields the better result on the fusion of feature extraction. When compared to the features collected using MFCC and LFCC separately, the SVM classifier has a success rate of 98% for the fusion model, which is 4% and 2% higher respectively. Whereas, random trees had taken little time for training and testing than compared to SVM and had an accuracy of 95% in the identification of insects within the three species.

3.1.3 Optoelectronic technology

Moore et al.[31] designed an instrument that is used to analyse and monitor two species of mosquitoes. The main idea was to differentiate between the species and the sex of insects with the help of wingbeat frequencies. Thus, they have used a device called an optical tachometer which produces amplified electrical signals by the reflection of insect's beating wings during the occlusion of a light source. The experiment was performed in a closed environment where the insects were placed in a plastic cage. This cage was placed in between the light source and the tachometer. The procedure was prolonged for 10 days for 15 insects of both the sex of two species placed in 22°C. They noticed various parameters of insects such as wingbeat frequencies, absolute amplitude of first four harmonics and absolute amplitude for first harmonic and relative harmonics for the next three consecutive harmonics. Though there was an overlap of frequencies of the same sex, the mean and species-specific frequencies had a marginal difference. Relatively they were able to achieve their goal with an accuracy of 85%, 81% and 82% respectively.

Batista et al.[18] also developed a system using an optoelectronic sensor. The objective was to automatically identify disease vectors to the species level and determine their sex using inexpensive sensors. First of all, the authors had research in identifying the insect species using traps that were found to be more man-powered as well as take time which may be greater than the life span of certain insects. Hence, they concluded the importance of inexpensive sensors. This led them to build a device that collects the data from a phototransistor whenever the winged insect comes in between it and the LASER. This was carried out for 15 days with one type of insect being a bumblebee and others belonging to the mosquito family placed under laboratory conditions. The data was collected in 12 hours to collect samples from dusk to dawn and check the ideal difference in appearance or the activity of a certain species. Though the bumble impatiens were classified with an accuracy of 100%, there was a significant overlap within the family of mosquitoes making its accuracy decrease by 5% on average. Similarly, Chen et al.[32] also used the same approach to classify an insect. The authors here had a different motivation compared to the previous ones. They identified the drawbacks of using an acoustic sensor which tends to have a strong interference to ambient sounds which led to the increased difficulty of classification. Hence, they arrived at this solution to classify insects of different species of mosquitoes within the same family. The data is collected with the same set-up as[18]. The data from the electronic board is converted to MP3 format to process in the Bayesian classifier. Though there was a noticeable amount of overlap within the frequencies of species, the results denote that there was classification accuracy of 98%. But, when the experiment was expanded to include more insect species, the accuracy dwindled to 79%.

3.1.4 RADAR technology

Smith et al.[33] and Champan et al.[34] used a Vertical-Looking Radar (VLR) to monitor the insects in high altitude. The VLR is comprised of a vertically oriented paraboloid reflector that produces a circularly symmetric beam. The upward-facing wave-guide feed was periodically rotated in the vertical axis by a small offset. This rotation of feed led to beam axis nutation and resulted in a conical scanning region. When an insect flies in this region, the radar scattering properties of the insect is detected by the receiver. These signals are processed and are used to extract the parameters such as speed, displacement direction, body alignment, body mass, wing-beat frequency, shape and size of the insect. These are the characteristics of insects that help us to identify the species.

Wang et al.[35] used S-band and W-band coherent radar to identify the wingbeat frequency measurements of insects. The back of the insect is capped with a piece of low-scattering polystyrene foam to keep the insect motion intact within the radar. The transmitted signal waveform for the W-band radar was a Frequency Modulated Continuous Wave (FMCW) with a sweep time of 0.5 ms with a signal bandwidth of 1.2 GHz. The transmitted signal waveform for the S-band radar was a Stepped-Frequency Pulse-Train (SFPT) signal with a signal bandwidth of 320 MHz. The wide bandwidth high-range resolution aids in clutter suppression and improves the radar detection effectiveness for weak targets. Also, they proved that the W-band is more effective than the S-band in identifying the wingbeat frequencies of smaller insects. The authors also validated that based on the micro-Doppler effect, the signal phase might be utilized to detect the frequency of insect wingbeats. The wing beating of insects is recorded by the radar which is used to intercept the wingbeat frequency of insects and ultimately used to classify them.

Hu et al.[36] used an experimental multi-frequency radar to compute the RCS value of insects to determine their names. The SVM classification model was used to classify a total of 23 species that were caught using a search-light trap. Each insect was adhered to a polyethene thread to its back and was suspended directly above the antennae, with its body axis parallel to the antennas' polarization direction. With uncertainties of 16.31% and 10.74%, the insect mass and body length may be derived from multi-frequency RCSs. With 13.37% and 7.99% uncertainty, the thorax width and aspect ratio can likewise be estimated. Moreover, for the statistical data of all 23 species, the right identification probability is greater than 0.5, and for 15 of them, they are greater than 0.8.

3.2 Discussion

The research on existing literature had led us to gain ideas and knowledge in insect detecting and monitoring applications. Based on the research, we derive a comparison table that maps the characteristics of insects and the most extensively used technology to identify, monitor and classify them which is shown in table 3.1. Image recognition is a visual-based technology that separates it from the other non-visual based technologies such as optoelectronic sensors, radarS and acoustic sensors. The visual technology allows us to capture the data and observe the physical parameters of insects including their shape, size and colour. These three parameters provide us with a lot of information in detail to identify the type of insect. It includes from the top part of the insect to their bottom parts such as their antenna and its types, wings and their type, colour and body shape and pattern. Apart from their physical characteristics, we can also deduce the body weight, wingbeat frequency, speed through image recognition technology. The length of the insect and the known biomass helps us to identify the weight of the insect. Wingbeat frequency and speed can be estimated through high-resolution cameras or video cameras which is captured through movement detection of insects. This is very challenging as insects move very fast during their locomotion. Non-visual technologies have different abilities to identify the properties of insects based on the sensors. Capturing and using the insect data through these technologies is very difficult compared to the image-based recognition system. Optoelectronic sensors can determine the wingbeat frequency of insects whenever the partial occlusion of light occurs. Additionally, wingbeat frequency further helps us to identify their wing size and the body shape of insects based on the theoretical formula. On the other hand, radars can produce outputs like distance, displacement and velocity. These extracts the properties of insects such as their speed and wingbeat frequency. Acoustic measurement is captured through microphones. As we all know, this helps us to extract the voice produced by insects. During their flight, the insects can produce sounds that can be captured through the microphone. From this sound, wingbeat frequency can be extracted by plotting the frequency spectrum.

Most of the existing technologies focus on trapping the insect species and then using them for identification in the indoor environment. This is mainly performed to reduce the complexity of the system as there will be no external parameters that would affect the capturing data of insects through the sensors. Although vision-based technologies are most widely popular due to their characteristics while compared to other non-vision based sensor technologies, the vision-based technologies make use of ALAN. These artificial lights are used in the system to capture the insect data during the night or when there is low light in the surroundings. As discussed earlier in Section 1.1, these artificial lights affect the migratory behaviour of insects and eventually kill them, which is against the motive of our research. Thus, the research will next focus on non-vision based sensors. The optoelectronic sensors have the tendency to capture the insect data only when the species flies in between the transmitter and receiver. This makes the system unidirectional. In the literature survey in the field of insect monitoring and detecting applications using optoelectronics sensors, the insects are either attached or caged in between the transmitter and receiver. Moreover, the sensor is used to capture the wingbeat frequency of the insects. As wingbeat frequency is inversely proportional to the size of the insect, there is a much higher probability that two or more insects fall into the same frequency category. This would make the system more difficult to identify the insects.

Moreover, capturing the wingbeat frequency for tiny insects would be difficult, as for these insects the amplitude modulation of the echo signal from the beating of wings would be quite weaker than compared to that of the other insects and further increase the computational complexity of the system. On the other hand, radars are most widely used in research topics in the migration of many animals. Similarly, there are many entomological radars that are used to monitor and track the insects with a range. These radars are moderately expensive compared to optoelectronics and acoustic sensors. Nowadays, radar also has become a technology to identify insects. The accuracy in the determination of insect parameters through radar is quite poor which had resulted in a decrease in the identification of insects. The determination in insect parameters falls below the threshold of identification making it less accurate.

In most of the scenarios, researchers had avoided acoustic technology because they are highly sensitive in nature and more prone to external noise. In some scenarios, the researchers have performed the collection of data in indoor environments to reduce the complexity of the overall system. Despite, its complexity, the unique features or sounds of insects due to their calling, mating, and lateral movement sounds which has enabled the researchers to focus on this acoustic technology. Additionally, the sound technology has the tendency to capture the raw data of insects from all directions using omnidirectional microphones which makes an edge over the other technologies. More importantly, this technology does not use light or any waves that could affect the behaviour of insects. In this literature, we also observed that there is a lack of research in outdoor environments using sound. Thus, this thesis will focus on capturing wild insects in outdoor environments. From Table 3.1, we can see that it is possible to extract the wingbeat frequency of flying insects which also helps us to improve the identification of insects. Thus, this thesis will focus on capturing airborne insects in outdoor environments.

Properties/ Technologies	**Image**	**Optoelectronics**	**RADAR**	**Acoustics**
Antenna	Yes	No	No	No
Body shape	Yes	No	No	No
Body weight	Partial estimation with the biomass and the length	No	Yes	No
Body colour	Yes	No	No	No
Angle of the body	Yes	No	No	No
Wing pattern/type	Yes	No	No	No
Wing size	Yes	Yes	Yes	Yes
Wingbeat frequency	Partially by movement detection	Yes	Yes	Yes
Wingbeat sound	No	No	No	Yes
Sounds emitted by insects	No	No	No	Yes
Speed	Partially by movement detection	No	Partial by acquiring the velocity obtained	Yes, with using multiple microphones in an array

Table 3.1: Properties and technology comparison

Chapter 4

Methodology

4.1 Background

For acoustic monitoring of insects, we collect the insect data in outdoor environments using a microphone. A microphone is a transducer device that collects the sound and transforms it into an electrical signal. A microphone consists of a diaphragm that moves when the sounds hit on their surface. It changes the air pressure, causing a change in electrical voltage producing electrical signals. Before we deal with these signals, we have to collect the data. To ensure this, we should have a microphone that will be suitable for our application which will be discussed in the next section.

4.2 Choice of microphones

Several microphone technologies are used to record sound. This includes carbon microphones, dynamic microphones, ribbon microphones, condenser microphones and Micro-electrical mechanical systems (MEMS) microphones. There are still different microphones, such as liquid microphones, crystal microphones which are outdated and converted to condenser microphones in recent years. As a result, the examination of numerous microphone technologies stated previously in this section will be evaluated for the application of identifying and monitoring insect species.

Table 4.1 shows a general comparison of different types of microphones. As the study deals with detecting the wingbeat sounds produced by the flying insects, there are certain characteristics and requirements to meet the demands of the goal. These

Types of microphones	**Sensitivity**	**Frequency spectrum**	**Cost (€)**	**Remarks**
Dynamic	Less	40 Hz-16 kHz	Cheap	Ideal for recording high/loud sounds
Condenser	High	20 Hz-20 kHz	Moderately expensive	Most responsive and used for high fidelity recordings
Carbon	Moderate	200 Hz-5 kHz	Cheap	More sensitive to higher frequencies
Ribbon	Less	20 Hz-20 kHz	Expensive	Collection of highly detailed sound without being oversensitive (guitar bass and other musical instruments)
MEMS	High	20 Hz-20 kHz	Cheap	Powerful response

Table 4.1: Microphone types comparison

are listed as follows:

- Directionality: It determines the sensitivity of sounds arriving from various angles at the central axis of the microphone. These are commonly known as 'polar patterns', which is a fundamental parameter to consider the microphone for this research. The polar patterns are either unidirectional, bidirectional or omnidirectional. Unidirectional microphones are confined to listening to only one specific region. Bidirectional microphones can receive the sound equally from the front and back of the microphones and whose polar pattern graph is similar to number 8. The area inside the loop of number 8 determines the region where this microphone tends to listen. Omnidirectional microphones have comparatively better sensitivity than the other two polar patterns as this tends to hear equally from all points in the sphere within a specific region. As the sound arrives from all possible directions concerning the microphone, the probability of these microphones picking up noise is also much higher.

Thus, the trade-off must be considered while selecting the type of microphone based on our application. As the study involves monitoring the insects using these sensors in outdoor environments, their behaviour and movement are not controlled. Thus, we consider omnidirectional microphones as this forms the base to listen to insect sounds from all possible directions of the microphone.

- Sensitivity: It is defined as the quantity of output (signal) to a given input. The sensitivity factor measures the right amount of data to be recorded. High sensitive microphone records sounds which are quite low and high noise as well. Low sensitive microphones are more robust to noise but do not record the sounds which are light. In this application, wingbeats sounds are feeble and hence it will be ideal to consider a highly sensitive microphone.

- Cost: It is ideal to have a low cost devices which will decrease the overall cost of the system. Thus, this study will also consider having a cost-effective system.

Ribbon microphones have only a bidirectional polar pattern which eliminates the need for this microphone in this application. Despite the omnidirectional polar patterns in dynamic and carbon microphones, they have some drawbacks. Dynamic microphones are less sensitive, whereas carbon microphones are highly sensitive to higher frequencies. Most of the wingbeat sounds lie in the frequency range between 20 Hz and 1200 Hz[31]. Thus, based on the requirements of this application, condenser microphones and MEMS microphones are considered over other microphones.

A condenser microphone is a device that consists of a thin diaphragm, charged metal plate and works based on the electrostatic principle. The diaphragm moves in response to the sound waves and this movement causes a shift in the distance between the diaphragm and the fixed metal plate. This alters the capacitance in the capacitor and is later amplified to produce a quantifiable electrical signal. The presence of a thin diaphragm makes it more sensitive to very low sounds. As the application is to detect the wingbeat of airborne insects, condenser microphones are comparatively a better option. There are two types of condenser microphones namely small diaphragm and large-diaphragm microphones. Small diaphragm microphones have a smaller membrane (less than 12.7 mm) and large-diaphragm microphones have a larger membrane (greater than 25.4 mm). We will consider one small and one large-diaphragm condenser microphone for this application and the comparison on types of microphones is as listed in table 4.2 and 4.3 respectively.

Microphone type	Manufacturer	Sensitivity	SNR	Frequency range	Cost (€)
AT4022	Audio Technica	-34 dB	81 dB	20 Hz-20 kHz	∼445
UMIK-1	minidsp	-32 dB	84 dB	20 Hz-20 kHz	∼110
NT55	Rode	-38 dB	79 dB	20 Hz-20 kHz	∼320
LCT 340	Lewitt	-36 dB	79 dB	20 Hz-20 kHz	∼350
CK-1	Avantone	-34 dB	78 dB	25 Hz-20 kHz	∼125

Table 4.2: Small diaphragm microphone comparison

The MEMS microphones work similarly to the condenser microphones where the diaphragm of these microphones are etched into a silicon wafer through MEMS processing. This diaphragm acts as a capacitor and the incoming sound waves cause the diaphragm to move. A semiconductor die that serves as an audio preamplifier translates the change in capacitance of MEMS to an electrical signal. These types of microphones are small that are being used to record the sounds. Applications of MEMS microphones can be seen in mobile phones, laptops, etc. Because of the miniature size, the antenna pattern is difficult to design and hence, all the MEMS microphones are only omnidirectional. All mobile phones tend to have similar performance and the OnePlus 9R containing an inbuilt MEMS microphone was used for this research.

Microphone type	Manufacturer	Sensitivity	SNR	Frequency response	Cost (€)
AT2050	Audio Technica	-42 dB	77 dB	20 Hz-20 kHz	∼300
Yeti X	Blue Microphones	-34 dB	80 dB	20 Hz-20 kHz	∼150
NT2-A	Rode	-36 dB	87 dB	20 Hz-20 kHz	∼280
CK-7+	Avantone	-38 dB	77 dB	25 Hz-20 kHz	∼300

Table 4.3: Large diaphragm microphone comparison

Microphone type	Manufacturer	Sensitivity	SNR	Frequency response	Cost (€)
Mobile phone	-	-32 dB	69 dB	20 Hz-20 kHz	(Inbuilt)
IM69D130	Infineon	-36 dB	69 dB	25 Hz-15 kHz	∼60
Camcorders	-	-34 dB	63 dB	40 Hz-20 kHz	(Inbuilt)

Table 4.4: MEMS microphone comparison

Based on sensitivity, Signal to Noise Ratio (SNR) and cost, minidsp UMIK-1, Blue Yeti X and microphone present in the mobile phone (OnePlus 9R) are chosen to monitor and detect airborne insects in outdoor environments. The microphones that we will be using in this work is as shown in Fig. 4.1. The UMIK-1 microphone is a small condenser circular microphone with a slim body and 18cm in height, 2cm in diameter. The YETI-X microphone is a large condenser microphone with its dimensions being 30cm in height and 10cm in breadth. The MEMS microphone is inbuilt in the phone and the dimensions of the phone being 16cm in length and 8cm in breadth. The microphone is present at the bottom part of the mobile phone.

(a) UMIK-1 microphone **(b)** YETI-X microphone **(c)** Inbuilt phone microphone

Figure 4.1: Microphones

4.3 Experimental components setup

This section discusses the system configuration that will be used to conduct the tests in the outdoor environment. Fig. 4.2 represents the actual hardware setup in front-view. The experimental component setup consists of three microphones to detect the insect wingbeat sounds of airborne insects. A UV light is also a part of this setup to attract the insects closer to the microphones. For the ground truth validation and to test the effectiveness of microphones to detect flying insects, two camcorders were utilised for this purpose. The camcorders were placed in a position to capture the visual information of insects that appear near the microphones. The three microphones are positioned next to each other in a linear array. As the wingbeat sounds are faint, these three microphones were kept near the light source as the flying insects get attracted to the light. The microphones are placed on the ground level, and the mobile phone is mounted on a tripod to match the level of other microphones.

Figure 4.2: Experimental component setup

The system consists of the following components.

- **Microphones:** In the experiments, we have used three different types of microphones to detect the sounds produced by the flying insects. As discussed in the Section 4.2, Blue Yeti X, minidsp UMIK-1 and mobile (OnePlus 9R) microphone will be used for this purpose.

- **Camcorder:** To effectively validate and compare the insect data, we will consider two camcorders which will be placed to get the straight and side view angle of the microphones. Sony 4K UHD camcorders were used to visually record the flying insects during the experiments. These camcorders also have a built-in night vision mode to record the insects during the nighttime. The frame rate of these videos is 25 fps which is stored mp4 file format. The pixel size of the videos is 1280x720 which is a typical high definition video resolution.

- **Light source:** As most of the experiments were conducted during the night, a Sylvania UV-A 20W fluorescent lamp was used during the experiment to attract the insects.

- **Interface:** The interface between the microphones and computer was done using the USB to type B and type C ports for Blue Yeti X and UMIK-1 microphones respectively.

- **Recording software:** The freely available and well-defined Audacity recording software[37] was used to record and save the sound data collected from the microphones.

- **Mobile speaker:** The sound to generate the sinusoidal sounds at various frequencies for indoor and outdoor ranging experiment was performed using inbuilt speaker in Realme 8. -28.6 LUFS is the power emitted by the speaker, which is reference to the maximum loudness.

4.4 Insect detection algorithm

The insect detection algorithm determines the occurrences of insects observed in the microphones over time. Fig. 4.3 is a flowchart that describes the flow of the process of the recorded audio signal. The algorithm to detect the insects from an audio file is shown in Algorithm 1. Fig. 4.4 denotes the step-by-step explanation of the insect detection algorithm. An identified insect as a mosquito from the annotated data was used for this purpose. The recorded raw audio signals are in time domain representation as shown in Fig. 4.4a. In the same figure, we could observe the noise present in the system and the occurrence of an insect is visible as a change in the amplitude (y-axis). The microphones are sensitive in recording the sounds in the environment.

Thus, the recording data will contain more noise. To minimise the noise present in the frame, a bandpass filter is applied to the audio signal to restrict the frequency band within 10 Hz and 1200 Hz (based on our literature survey). The frequency-domain of the signal before and after applying bandpass filter is shown in Fig. 4.4b and Fig. 4.4c respectively. Applying this filter will restrict the audio signal within this specific range and not overlook audio frequencies (unwanted data) beyond the range where insect wingbeat frequency is not observed.

A sliding window technique was used to process the algorithm to detect the flying insect sounds. The sliding window size (Ws) was set to one second, corresponding to 44100 samples. The overlap between windows was set to 50% to the window size. The window size was determined by analysing the videos in terms of the number of insects that re-appeared. Since most insects reappeared after 1 second, this window

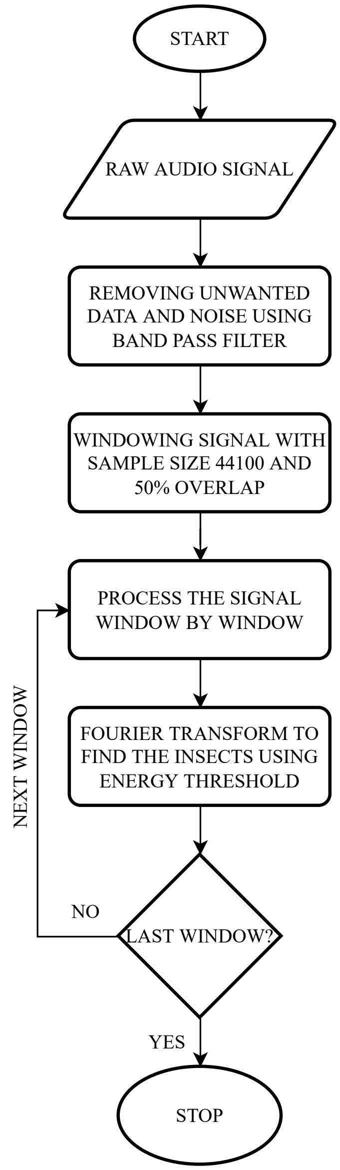


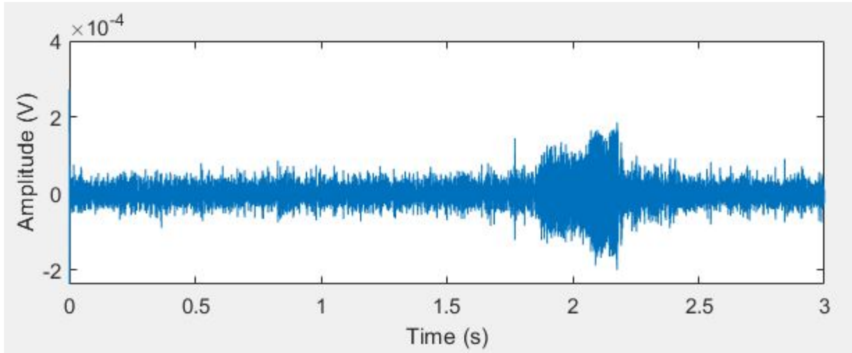
Figure 4.3: Flow of process of the recorded audio signal

size was used in the algorithm. The effect of change in window size will be discussed in detail in Section 6.2.1.

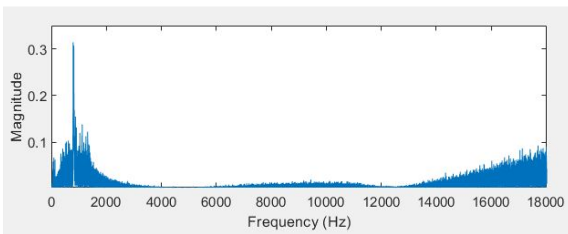
To determine the presence of insects, we look for the peaks in the audio signal in the frequency domain. A peak is defined as a local maximum value of the window which will be larger than their neighbouring values. We apply Fast Fourier Transform (FFT) to convert the time-domain representation of the windowed signal into the frequency domain. This is done to identify the peaks of the signal in the frequency domain. A larger peak is observed whenever the insect is present in that time frame. This is due to the result of the energy produced by the insect during its flight. The peaks above the threshold are visible with an inverted triangle shown in Fig. 4.4d. As there will be multiple peaks for a single insect recording, we will consider the highest peak and will discard the rest of the peaks shown in Fig. 4.4e. This is done to reduce the number of false positives and improve the performance of the system. Also, we could observe peaks due to various noises, which is considered false positives after comparing the data with the videos recorded from the camcorders. The occurrence of insects in the signal is determined using the peaks above a certain threshold based on the energy level (Es). The threshold (TD) was set based on the average energy level observed in the annotated sound segments containing the airborne insects. The energy level is calculated in decibels. Although we eliminated the signals above 1200 Hz, we can see from the Fig. 4.4e that there is a small amount of energy (-70dB) is present in the filtered signal. As the energy of the eliminated signal is very low compared to our required signal, this will not affect the performance of the insect detection algorithm. Apart from identifying the peaks of the insects, the frequency domain signal will also help us to identify the fundamental frequency of insect wing-beats. The fundamental frequency may be used to classify the insect species.

Algorithm 1 Insect detection algorithm

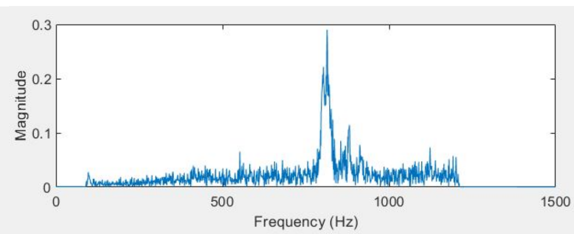
```
Load Audio file
Convert stereo file Mono audio file
Initialise step size Ss = 0
Apply Band Pass Filter
frames = Mono audio file/Ss
for i = 1 : length(frames) do
    window=filteredsignal(Ss:Ss+Ws-1)
    f=fft(window)
    Es = 20*log10(abs(f))                ▷ determines the energy of the window signal
    [peaks, location] = findpeaks(f, Es, TD) ▷ returns the peaks of insects above certain threshold
    Mark the timestamp from location of peak
    Mark fundamental frequency
end for
```



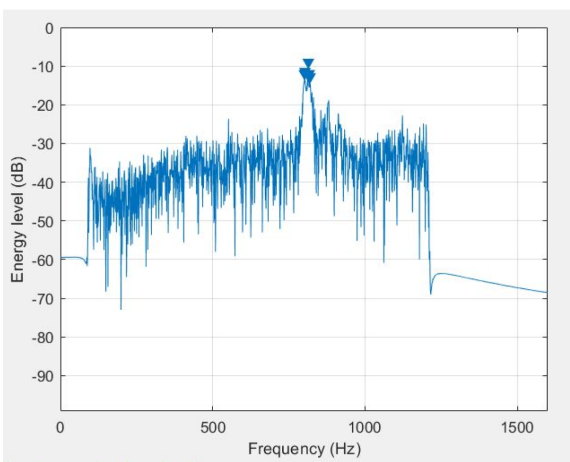
(a) Time domain signal



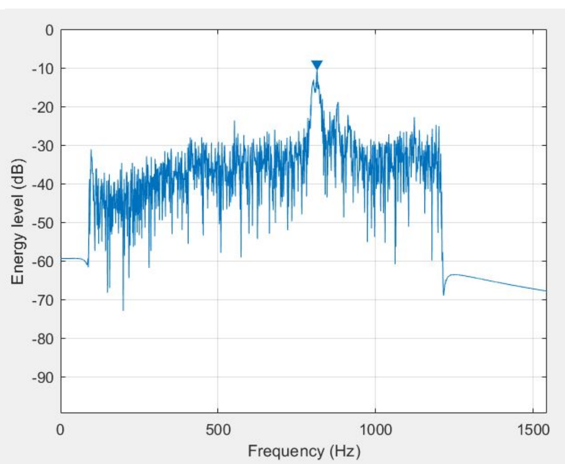
(b) Before applying bandpass filter



(c) After applying bandpass filter



(d) Multiple peaks for single insect



(e) Single peak for single insect

Figure 4.4: Step-by-step working representation of insect detection algorithm

4.5 Performance metrics

The metrics that evaluate the performance of the system are described as follows:

- Positives (P): It denotes the number of times that insect has been observed in the camera frame over the period of the experiment. The value of P is incremented every time an insect appears close to 15cm from the microphones. The mathematical expression is given as

$$P = TP + FN \tag{4.1}$$

- Negatives (N): It denotes the number of times that insect is not observed in the camera frame over the period of the experiment. The mathematical expression is given as

$$N = TN + FP \tag{4.2}$$

- True Positive (TP): It defines the detection of the flying insect by the algorithm and the presence of the insect in the camera frame.
- True Negative (TN): It defines the ability to correctly identify the absence of insects when there is no insect present in the camera frame.
- False Positive (FP): It defines the detection of the flying insect by the algorithm without the presence of the insect in the camera frame.
- False Negative (FN): It defines the ineffectiveness of the algorithm to detect the flying insect in the presence of the insect in the camera frame.
- Recall: The ratio of true positives to total occurrences of insects (ground truth) determines the recall factor also known as sensitivity or true positive rate. The mathematical expression is given as

$$Recall = \frac{TP}{P} = \frac{TP}{TP + FN} \tag{4.3}$$

- Precision: It defines how frequently does the algorithm get it right when it predicts true? The mathematical expression is given as

$$Precision = \frac{TP}{TP + FP} \tag{4.4}$$

- F1 score: It is defined as the weighted average of precision and recall whose mathematical expression is given as

$$F1\ score = 2 * \frac{precision * recall}{precision + recall} \tag{4.5}$$

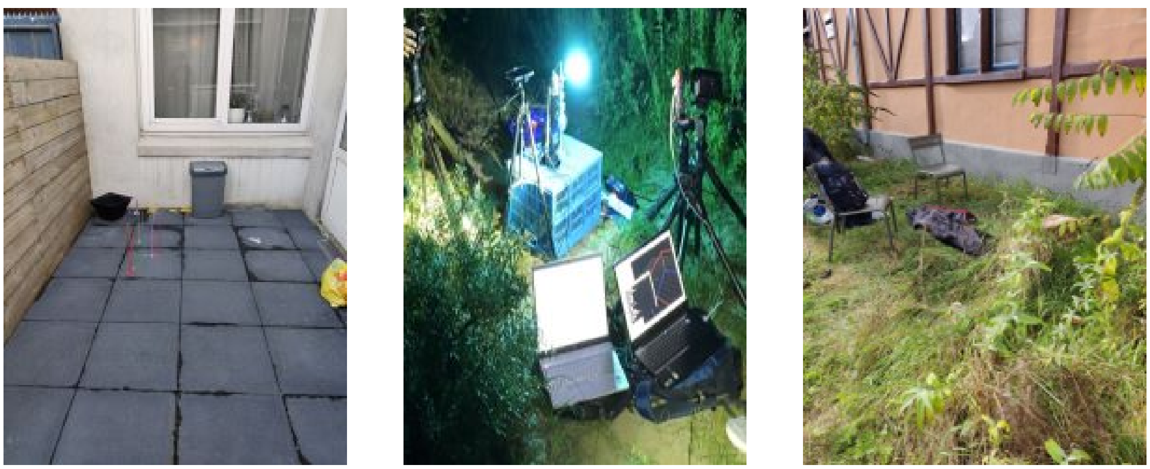
Chapter 5

Data acquisition and annotations

This chapter will first discuss how, where and when the insect data were collected in the outdoor environments using microphones. Later, this chapter also discusses how the insect data were annotated with the recordings of microphones and camcorders.

5.1 Data acquisition

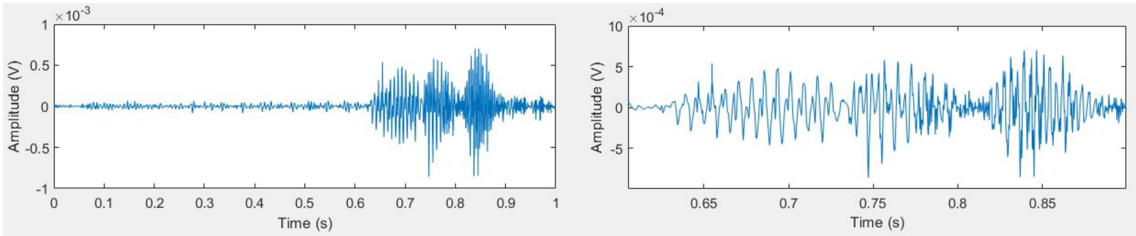
The tests were conducted in open areas; namely in urban and suburban environments. These were predominantly conducted during the nighttime to attract a large number of insects near the sensors. The preliminary testing was carried out in a garden. The yard is rectangular, measuring 4m x 2m. The location is a common household urban environment. For the suburban environment, the system was also employed in open fields in the inner dune area of Katwijk aan Zee. The experiments at these locations were conducted during the night and hence, a UV light source was used to attract the insects. Later, the third experiment was conducted in the vegetation region at Artis Zoo located in Amsterdam. This experiment was performed during the daytime because of the timing restrictions of the Zoo. The experiment conducted at the inner dune area of Katwikjk ann Zee and Artis Zoo were identified as they were thought to be good spots to locate insects in the region. The Fig. 5.1 shows the multiple tests environments where the data of airborne insects were collected. In the dunes area and the Artis zoo experimental site, the ground was uneven with lots of grass present. Thus, a card box measuring 30 cm in height was used to place the microphones. This was done to make sure the three microphones were placed in the linear array with approximately equal height to one another. The environmental noise at Artis Zoo would be comparatively higher than all the test scenarios. This area is nearby to a tram station, a lake and a road adjacent to each other. The microphones and the camcorders continuously recorded the events during the process of the experiment. The microphone recording was recorded and saved using the freely available Audacity recording software. The sampling rate was set to 44.1 kHz. Thus for every second, there will be 44100 samples of the data that will be recorded. If we increase the sampling rate, there will be a computational complexity. This would greatly slow down the process and decrease the performance of the overall system. At the same time, if we decrease the sampling rate, there is a greater possibility of data loss which will ultimately degrade the quality of data collection samples. Hence, a sampling rate trade-off of 44.1 kHz was considered. All the microphone recordings were stored in wave file format instead of the usual mp3 format storage. This is because the wave file is uncompressed and will give us more insights while extracting the useful parameters of flying insects.



(a) Urban environment **(b)** Suburban environment **(c)** Artis Zoo site

Figure 5.1: Test environments

Fig. 5.2 shows an example of the representation of collected insect data during the experiment. This figure represents the wing pattern of the airborne insect. This data is the result after applying the bandpass filter and the zoomed version of the same insect pattern is shown in Fig. 5.2b.



(a) Observed insect pattern **(b)** Zoomed portion of the (same) insect pattern

Figure 5.2: One-second sample of insect occurrence

5.2 Environmental conditions

The tests in the outdoor environments in urban and suburban areas were conducted during September and October. The tests were conducted in the backyard of a house, Kaatwijk aan Zee and Artis Zoo experimental site. The measured temperature conditions during the conduction of experiments were in a range between 14° C and 20° C. The wind speed during these experiments was also found to be in the range between 8km/h and 16 km/h. The wind speed observed during the experiment were moderate which will not have a great effect on the flight of insects. The exact weather conditions of the particular experiment in three different environments are as shown in Table 5.1.

Parameter	**Urban environment Day 1**	**Urban environment Day 2**	**Suburban environment**	**Artis Zoo site**
Temperature (°C)	20	18	17	13
Wind speed (km/h)	8	15	8	16
Noise (dB)	64	66	57	71

Table 5.1: Environmental conditions

5.3 Data Annotations

The sound data were manually annotated by a person who was not an entomologist. The annotation of sound data was performed using the Audacity software[37]. The sound data was visualized in both time and frequency domain along with the video to determine the presence of an insect in the vicinity of the camera. The spectrogram of the signal will help us to visualise the energy spread across various frequencies and were also used in the data annotation process. A spectrogram is a graphical representation of the range of frequencies with its signal strength over time. A spectrogram is generated by converting the signal in the time domain to the frequency domain using FFT. An example of labelled data of a moth is shown in Fig. 5.3.

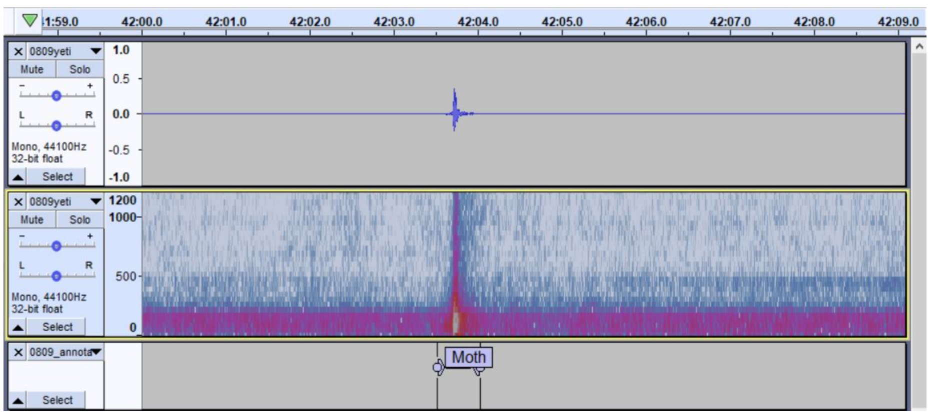
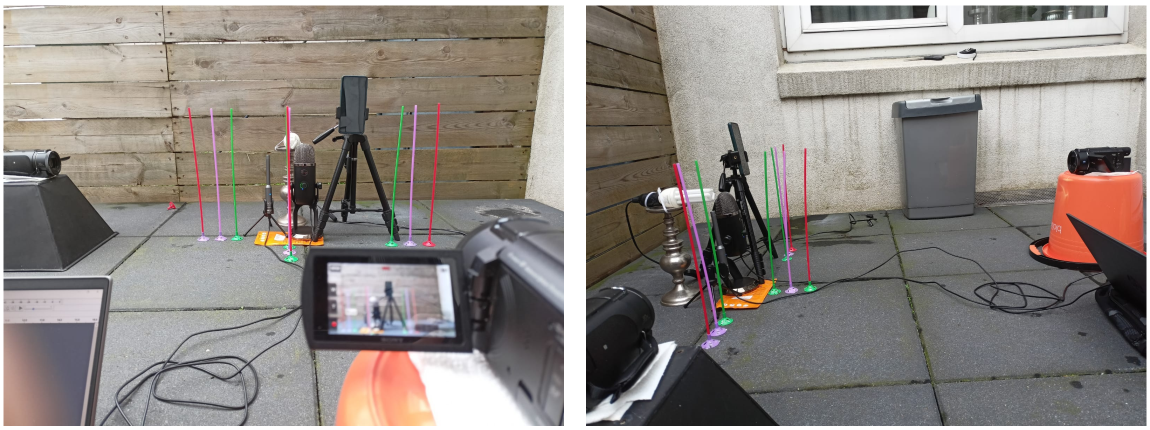


Figure 5.3: This figure represents the screenshot of the labelling application in the occurrence of a moth insect during the experiment. The above part of the figure represents the time domain of the signal and the lower part represents the spectrogram of the signal. The signal is filtered using the bandpass filter. The value on the x-axis is time in both representations. The values on the y-axis correspond to the amplitude of the signal and the frequency of the signal in time domain representation and spectrogram respectively. The signal in the above part is flat because of the less noise present in the environment whose energy is negligible to occur/observe as a change in the waveform. The colour in the spectrogram view represents the energy level of the insect wingbeat frequency. A dark colour towards yellow depicts that the energy is more prominent, which is observed as a result of the occurrence of the insect. Here, we can see the presence of the insect leads to a change in the waveform in the above part as well as the energy portion is more distributed in frequencies above 150 Hz in the bottom portion. The rest of the colour in the spectrogram (blue and pink) represents the noise in the environment.

The timestamps of the sound data and the video data were used for synchronization. The act of snapping fingers in front of the camera was used for this purpose. The ground truth of insects was considered for the insects that appeared close to 15cm from the microphones. The distance was verified by placing the balloon sticks acting as measuring sticks near the microphones. These sticks were placed at every distance of 5cm equally positioned from the microphones as shown in Fig. 5.4. When the same insect reappears near the microphone, it is validated as a separate ground-truth measure from the videos analysed.



(a) Front view **(b)** Side view

Figure 5.4: Representation of measuring sticks near microphone

At first, videos of the recorded insect were manually visualised to determine the threshold on the energy level of airborne insects. This measurement task was computed for more than 10 insects. The energy level of these flying insects was determined individually. An average of these computed energy levels was used to set the threshold for the insect detection algorithm. After setting the threshold, the algorithm was used to determine the presence of insects. The insect detection algorithm and the videos from the camcorder were used to annotate the rest of the audio segment. The timestamps were determined for every occurrence of insects. These timestamps were also verified using the video data for the ground truth of insects. Later, the recorded timestamp was used as a reference to manually label the sound data of insects. Similarly, the sound data of other airborne insects were also labelled.

The validation of data from the camera recordings will also enable us to identify the types of insects that appeared near the microphones. Although the exact species name is difficult to find using just the visual traits of insects, it is possible to identify them by common names such as mosquitoes, butterflies, common flies (houseflies and dragonflies) and much more. The Table 5.2 describes the data of such insects observed and identified visually from the camcorders.

Environment	**Bees**	**Bugs**	**Butterflies**	**Common flies**	**Mosquitoes**	**Moths**	**Unidentified**	**Total (N)**
Urban	0	3	1	12	17	4	32	69
Suburban	0	0	4	10	13	2	22	51
Artis Zoo	5	0	0	4	0	0	20	29

Table 5.2: Identified insects

Table 5.3 represents the data on the number of windows with insects and non-insects data. This was visualised during the data annotation process. Although we observed a cumulative of 149 insects from the three experimental sites, the ratio of insects observed to the overall duration of the experiment is very less. Thus, the number of windows with no insects is much larger than compared to that of windows with actual insects.

Environment	**Insects**	**No insects**
Urban	69	17712
Suburban	51	7038
Artis Zoo experimental site	29	35642

Table 5.3: Windowing data

The videos recorded from the camcorders were annotated by two people individually. This helped in computing the total number of insects that occurred in a time period. However, the labelling was performed by one person to reduce the complexities during the labelling process. The labelled data was extracted and stored in a plain text file. A small portion of annotated data is as shown in Fig. 5.5. The text file consists of the start and the end time (both in seconds) of insects that appeared along with the type of insect which was labelled and observed through visual data from the camcorders. The text file can be extracted along with the sound data which will enable us to keep track of annotations.

2428.919060	2429.336023	Unidentified
2433.791575	2434.542109	Common fly
2434.661241	2435.209250	Common fly
2523.522100	2524.034369	Moth
2554.520351	2555.008794	Moth
2563.693546	2564.336861	Bug
2608.201411	2608.582635	Mosquito

Figure 5.5: A portion of annotated segment which consists of start time (to the left), end time and the type of insect observed through the videos.

Before we proceed with the insect data, we must ensure whether that particular data was a true measure? We have the timestamps recordings of the probable insect detected using our algorithm. Now, the videos from both the camcorders were analysed. The manual visualisation of camera recordings is performed which enables us to determine the timestamps in presence of the actual insects. A comparison of timestamps of audio insect data from the algorithm and timestamps of captured insect frames is performed. This verification helps us to visualise the insect data to determine the performance of the overall system.

Chapter 6

Experiments and results

This chapter explains the experimental methodology for each test as well as the analysis used to acquire some relevant insights from the acoustical data collected using three different types of microphones.

6.1 Range detection experiment

This section deals with the maximum range detection among three microphones in two different settings; indoor and outdoor environments. This experiment will determine the feasibility of three different microphones in this insect monitoring and detecting application. The evaluation of these microphones is performed using the maximum detection range. The setup for conducting the experiments in the indoor environment is as shown in Fig. 6.1, and for the setup of microphones in an outdoor environment is in system setup shown in Fig. 4.2.

From Fig. 6.1, we can see the presence of a wall behind the microphones. The distance between the wall and the microphones was measured to be around 50cm. Generally, the walls have the tendency to absorb and reflect the sound waves that might have an impact on the energy of sound waves. When the signal hits the wall, most portion of the energy is lost in absorption and a little amount of energy is reflected from the wall. As the energy generated from the mobile speaker is very low, the probability of sound reflected from walls for these signals is particularly low. Hence, the reflected energy of the signal will fall below the threshold if the reflected sound wave hits the diaphragm of the microphone. Thus, the reflected signal will not have a significant effect on our application concerning range detection.

Figure 6.1: Indoor setup

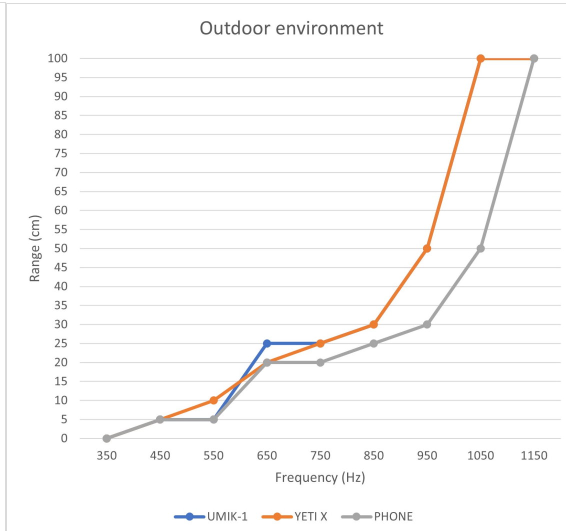
From the literature study, we know that the wingbeat frequency of insects ranges between 10 Hz and 1200 Hz, various frequencies within this range at certain intervals were mimicked through a mobile speaker. The frequencies generated from the mobile speaker was purely sinusoidal. As this test records the performance of these three microphones concerning range, the pre-recorded wingbeat sounds of actual insects were not considered. This is because certain parameters may have an impact on the performance of these microphones during this experiment. These parameters include the conditions of recording the wingbeat sounds of those insects, the choice of microphones and the environment. As these parameters would be difficult in addressing and validating in this experiment using these three microphones, the sinusoidal signals were considered.

In our application, since the sound produced by the insect wingbeats is feeble, it is very important to manage the energy level of insects with the sound generated through the mobile speaker. From the annotated data verified from the videos, the energy of insects that were in close proximity of less than 5cm from microphones were measured. This measurement task was computed for more than 10 insects to measure the energy level. Then, an average of these energy levels was considered to generate a similar energy level from the mobile speaker. So the mobile phone was placed near the microphone within 5cm range from it to calibrate the energy level produced by the mobile's speaker. The volume setting in the microphone was adjusted by comparing the energy output level from the mobile speaker with respect to the energy level of actual insects in the same range. When the energy level matched, the same volume setting was used for the indoor and outdoor ranging experiment.

Fig. 6.2 shows that condenser microphones have a better detectability range in the indoor environment and outdoor environment compared to the MEMS microphone. Despite the frequency response of these microphones being between 20 Hz and 20 kHz, the ability of these microphones to pick up the feeble sounds with frequencies less than 150 Hz is quite poor. The lower intensity sound generated with frequencies less than 150 Hz is not heard by the microphone even within 5cm from it. We can see from the graph from figure 6.2b that the detection of UMIK-1 and Yeti X superimpose with each other and tends to slightly outperform the MEMS microphones. There is a drastic change in the maximum detection range observed in indoor and outdoor environments. This is because of the ample amount of noise present in an open environment. The cause of this noise is observed to be wind, electronic noise from microphones, whispering sound, the interaction of human beings 3 - 5m apart from the microphones and much more. The level of noise present in an indoor environment accounts for 37 dB whereas, the level of noise present in an outdoor environment is observed to be 64 dB. The sound level in the audio signal was computed using 'splMeter', a MATLAB inbuilt function that measures the sound levels of the audio signal. Also, the presence of noise such as natural sound and wind sound is widely found in frequencies up to 350 Hz. Hence by these factors, the performance of all three microphones is greatly affected in the lower frequency range up to ∼350 Hz.

The indoor range detection graph in Fig. 6.2a limits to 850 Hz. This is because the maximum detectable range for this particular frequency (850 Hz) was observed to be 4m. Above this frequency, the maximum range of detection of all the microphones is greater than 4m. As the wingbeat sounds of insects in an indoor environment are not expected to be heard in a microphone greater than 4m[38], the range in the indoor environment is limited to 850 Hz. On the other hand, we could see a drastic decline in the maximum detection range in outdoor environment which is 1m. The maximum range increases as we increase the frequency. This is because the amount of power generated by the mobile speaker increases as the frequency increases as shown in Fig. 6.3. As the power increases towards the positive value, the signal becomes stronger in that particular frequency. Thus, higher frequencies generated through mobile speakers tend to have a higher range.

(a) Indoor environment



(b) Outdoor environment

Figure 6.2: Maximum detection range of three microphones

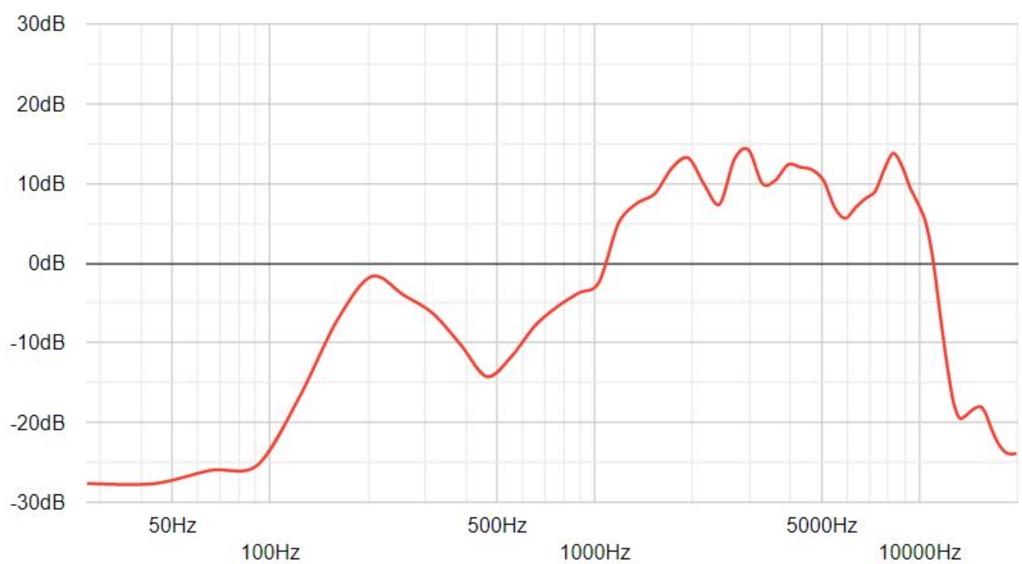


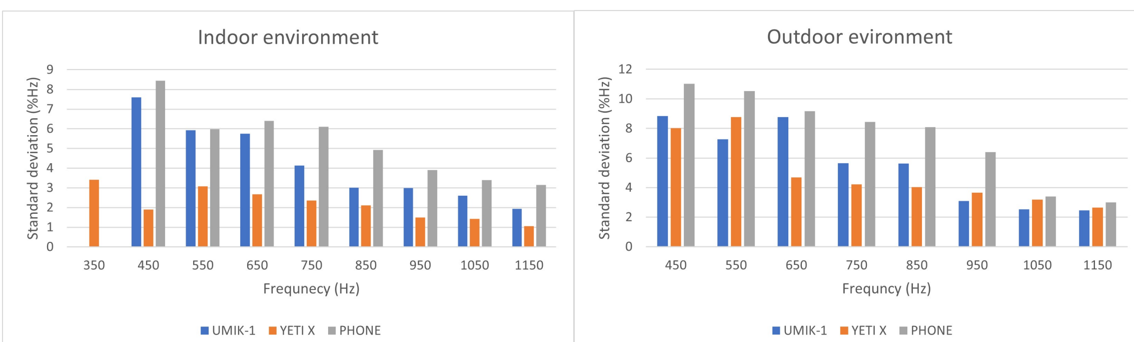
Figure 6.3: Speaker's power output across varying spectrum[1]. The x-label determines the frequency range and the y-label determines the power output at each frequency.

The standard deviation of the detected range of frequencies is measured using the mathematical formula Eq. (6.1).

$$SD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{6.1}$$

where,
N = Number of samples
x_i = Observed frequency
$\bar{x}$ = Average frequency

The standard deviation performance of microphones at the maximum range was deduced from 10 samples. Each sample is a measure of 0.5 seconds. The maximum range is determined from the previous data in Fig. 6.2. The maximum range of each microphone in indoor and outdoor environments varies for each frequency. From Fig. 6.4, we can infer that as the frequency increases, the standard deviation gradually decreases for all three microphones in both indoor and outdoor environmental scenarios. Based on the observation, the performance of large and small condenser microphones are comparatively the same and better than that of MEMS microphone.



(a) Indoor environment **(b)** Outdoor environment

Figure 6.4: Standard deviation graph for maximum range detection

6.2 Airborne insect detection

This section deals with evaluating and analysing the performance of the microphones in insect detection applications in outdoor environments. The insect detection experiment was conducted in three different scenarios as we have discussed in Section 5.1. Table 6.1 corresponds to the performance metrics of the airborne insects in three different environments. The precision factor and a poor F1 score are observed as a result of external noise in the surroundings. Similarly, a large number of true negatives is observed due to the vast amount of raw recordings. The ground truth was observed using the videos recorded through the camcorders.

Parameter	**Urban environment**	**Suburban environment**	**Artis Zoo experimental site**
TP	53	43	17
TN	17712	7038	35642
FP	384	77	367
FN	16	8	12
Recall	0.76	0.84	0.58
Precision	0.12	0.35	0.044
F1 score	0.20	0.49	0.08

Table 6.1: Overall system performance in detecting airborne insects

Urban environment - Backyard
The first experiment with actual insect targets was carried out in a backyard of a house. This location will be highly prone to the surrounding noise as this location is a common household urban environment. These unwanted sounds include vehicular sounds, helicopter sounds, mechanical sounds and human vocal sounds, which is considered background noise in our system.

From the Table 6.1, we could see a relatively larger number of peaks to be observed in the urban environment. This occurrence of peaks is due to the significant amount of surrounding noise present in the environment that we have discussed earlier. In the urban environment, a good recall rate of 76% is observed. The microphone relatively recorded smaller insects such as mosquitoes and common flies. However, the tiny insects (smaller than the size of mosquitoes) were not recorded. Furthermore, the increase in the amount of wind speed accounted for a 7% increase in the number of peaks observed on the second day of the experiment when compared to Day 1. If the wind speed increases further, the performance of the system would deteriorate even further. To compensate for this effect, a pop filter made of nylon was introduced to reduce the impact of wind noise. This filter covered the whole region of the microphone's diaphragm. The experiment with pop-filter was conducted in conditions with wind speeds greater than 20 km/h. As expected, the introduction of a pop-filter did reduce the noise caused by the winds, but it relatively decreased the performance of the system. Since the wingbeat sounds of insects are feeble, the insect sound is also filtered by the material and thereby decreasing the overall detection and the performance of the system. Despite these insects were flying very close to the microphone within 5cm of range, the microphone was not able to detect the sound produced due to their wingbeats when the microphone was covered with a pop filter.

Suburban area - Katwijk aan Zee

The next experiment was conducted in Kaatwijk aan Zee. The suburban dune area was located a bit far away from an urban household environment and thus there will be a little reduction in environmental noise compared to our previous test case. However, the vehicular and jet aeroplane sounds can be easily noticed by the sensors. As the experiment was conducted during the night, the other sounds emitted by insects (such as katydids sounds for calling) will also be heard in the sensors. These katydids sounds were observed throughout the course of this experiment. These katydids sounds can be easily filtered as they do not lie in the wingbeat frequency band where airborne insects are observed. Since it was a suburban dunes area, a large number of insects were found in this experiment and the majority of the insects were medium-sized insects with their size measured between 1cm and 3cm. The size measures are approximate values from the camcorder visualised data and the measure was performed with mosquito size and a moth size as a reference.

The medium-sized insects such as moths were detected by the microphones along with the smaller ones like mosquitoes and common flies. The wingbeat sounds in the occasion occurrences of larger insects which includes some unidentified insects were rarely heard from the recorded sound data from microphones. The rare scenarios include when these larger insects were flying very close (approximately within 5cm) to the microphones. However, the occurrences of large insects were not determined by the insect detection algorithm due to the amount of noise present at that instance. A high recall rate of 84% was observed in this environment even though a small amount of larger insects were not detected by the algorithm. Hence, due to the less noise present in the surroundings, a comparatively fewer number of peaks were observed. This also had significantly observed a better precision of 35% with an F1 score of 49%.

6.2.1 Effect of window size performance

The performance metrics for airborne insect detection was performed with a window size of 1 second as discussed in Section 4.4. In this section, we will perform and analyse the system's performance with varying window sizes. Initially, the window size was halved to 0.5 seconds corresponding to 22050 samples and later it was doubled from the original window size to 2 seconds corresponding to 88200 samples. Then, the performance metrics were calculated in a combination of all the environments which are shown in Table 6.2.

Parameter	**0.5 seconds**	**1 second**	**2 seconds**
Recall	0.79	0.75	0.61
Precision	0.12	0.12	0.09
F1 score	0.20	0.20	0.15

Table 6.2: Performance metrics on varying window size

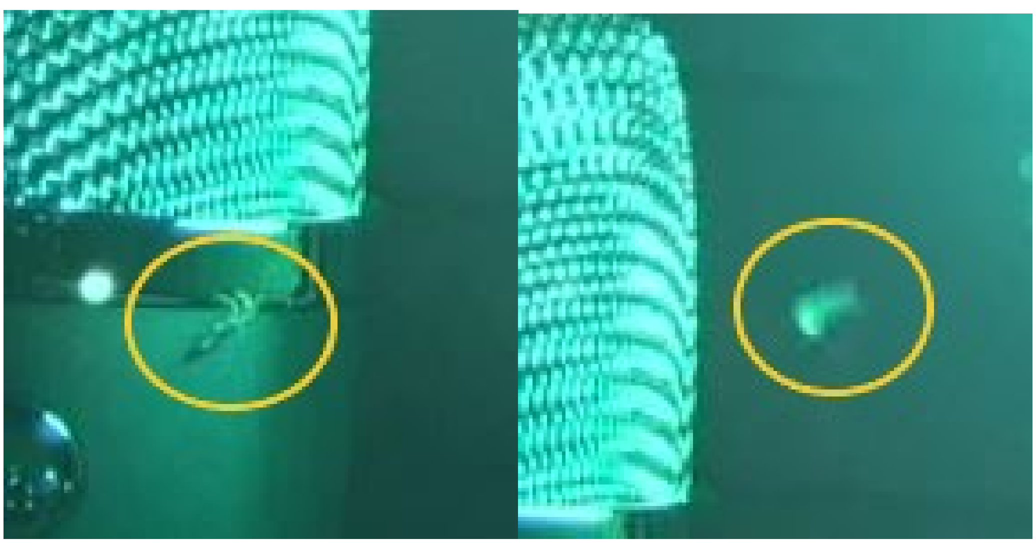
From the Table 6.2 it is evident that the performance of window size is almost similar for 0.5 seconds and 1 second whose F1 score is observed to around 20%. A significant decrease in recall and F1 score is observed when the window size is increased to 2 seconds. This recall factor with a window size of 2 seconds was observed to be 61% with an F1 score of 15%. The main reason behind this is the re-occurrence in a certain time interval which is verified from the ground truth of insects. The same insect appearing again within the same window size will lead us to a decrease in the number of true positives and thus affect the recall factor of the system. The performance of the system with varying window size is based on the number of insects that has re-appeared in a certain time interval. If these insects had appeared again only after 2 seconds, then the performance of the system in all the window sizes that we have considered would be similar.

6.3 Insect classification

In this thesis, we did not perform the insect classification. However, in this section, we will discuss how the recorded data can be used to classify insect species. The classification procedures require machine learning techniques to identify the insect species. Different type of machine learning techniques that can be used in insect classification is discussed at Section 2.2. The classification stage requires features of the insect to be recognised and placed in the order of the taxonomical chart. Every sub-level in the taxonomy chart will have its own characteristics that will lead us to order the insects up to the species level, which is the final stage of the classification procedure. The classification stage involves three sub-stages namely training, validation and testing. Some samples of extracted features are used to train the classifier which helps to classify the species. The validation set is used for the unbiased evaluation of the classifier model and to improve the quality of the data. In the testing phase, the classifier will compare the features of the insects from the training set and give us output in determining the unknown insects.

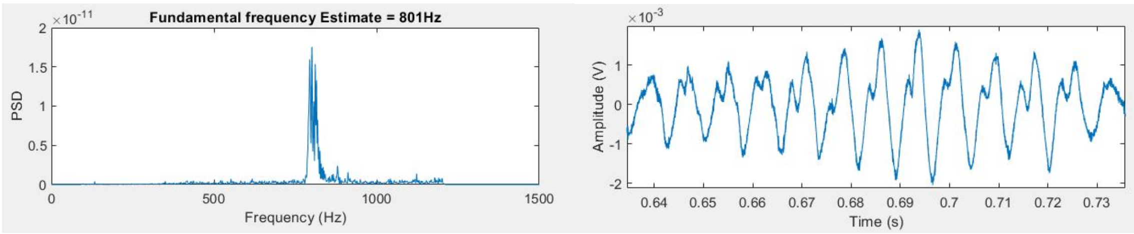
The beginning stage involves detecting the sounds produced by airborne insects. In this research, we determine the occurrences of insects using the insect detection algorithm as discussed in Section 4.4. This involves segregating the insect data from the raw recordings of the collected data in the outdoor environments. Also, this stage helps in processing only the required data. The identified sound segments of insects are processed by extracting the features of the insects. This can be used by detecting the fundamental frequency of the insects. The fundamental frequency is the lowest frequency at which the insect beats its wings. This identified feature of insects can be used to train the classifier. Any trained classifier can now be used for insect classification for classifying unknown insect species. The mosquitoes have wingbeat frequency in the higher range of the spectrum compared to that of a moth which will lie in the lower end of the spectrum. As a result, classifying these insect species will be easy, and the classifier will provide accurate results. But, when a housefly and a mosquito is observed, it is very difficult to identify the species using just the wingbeat frequency obtained from these two insects. Since, the fundamental frequency of a mosquito is also similar to that of a housefly, classifying them is becomes trouble and affect the performance of the overall system. This is overcome by adding extra features to the classifier so that it can make decisions with high accuracy.

A general framework for adding features can be made just like the primary classifier. This will enable us to train the classifier with multiple features extracted from insects. The wingbeat frequencies observed for various insects are moderately well separated within the size of insects. As the size of insects is inversely proportional to the wingbeat frequency, the size of the insect can also be determined with the fundamental frequency of insects. It is possible to add another feature to the classifier which is the wing pattern of the detected insect species. These wing patterns are species-specific and will help the classifier to make decisions more precisely. The performance of the system at this stage with these features would have relatively improved the classification accuracy. From this, we can infer that as we increase the features on training the classifier, better will be its accuracy in classifying the unknown insects down to species level in the taxonomy chart. An example of an unidentified insect species is shown in Fig. 6.5. The wingbeat frequency and the flight pattern of this unidentified insect species are shown in Fig. 6.6.



(a) Insect sitting on the microphone **(b)** Insect flying near the microphone

Figure 6.5: Occurrence of an insect species - Unidentified insect



(a) Fundamental frequency of the insect species **(b)** Flight pattern of the insect species

Figure 6.6: Features of a unidentified insect species

6.4 Limitations

- The system was tested in average weather conditions observed in the months of September and October. This limits the test of microphones in adverse weather conditions such as high winds, cyclones and rains. These factors could relatively affect the performance of microphones with more environmental noise and degrade the collection of data in outdoor environments.
- As the configuration of the system was fixed, the parameters of the microphone such as pre-amplifier, gain factors were not altered.
- The algorithm used to determine the insect species from the raw recordings was based on absolute/hard threshold. This absolute threshold did affect the performance of the system with a large number of false detections.
- The effect on the performance of multiple insects was limited to this study due to a lack of data on one or more insects appearing near the microphones at the same time during the conduction of these experiments.
- As the motive of this research was to detect and monitor the insects in an outdoor environment, classification techniques to determine the unknown insect species is limited to this research. Similarly, the research was focused on sounds produced during the flight activity of airborne insects. Thus other sounds apart from their flight activity by insects such as katydids during the experiments were filtered.

Chapter 7

Discussion

In this chapter we will discuss the overall performance of the system by answering the sub-questions. Later, we will discuss the effect of several parameters in insect monitoring and detecting insects in an outdoor environment.

7.1 Performance of the system

What is the suitable sensor technology to detect and identify the airborne insects in urban and suburban outdoor environments?

The selection of sensor technology is a vital procedure to conduct the experiments and validate our motivation. The motive of this research is to detect the flying insect species without using ALAN. Current methods to detect the insects such as image recognition technology use light sources and trapping methods that will affect the insect. When a RADAR is used, it sends out signals to receive the data of the object hit by these waves. When these waves hit the insects, the power of these waves is absorbed by the insects which induce the dielectric heating for the insects resulting in affecting the insect species biologically. Similarly, exposure to LASER lights from LiDAR will eventually affect the insects physically. Thus, these methods on a long exposure may affect the insects and kill them. Moreover, LiDAR are highly expensive in terms of cost. On the other hand, acoustic sensors are cost-effective, do not use artificial lights nor emit any harmful rays that might affect insects biologically or physically. Thus, this sensor technology is considered over other technologies to detect and monitor airborne insects in outdoor environments as discussed in Chapter 3.

What is the feasibility of this technology in insect monitoring applications?

To measure the feasibility of three different microphones used in this experiment, the tests were conducted for these microphones using purely sinusoidal signals. These signals at various frequencies from 50 Hz up to 1150 Hz (with an interval of 100 Hz) were mimicked through the mobile speaker. The signals with high intensity would travel a long distance and can be easily heard by the microphone. As the application was to detect the sounds produced by the flying activity of insects, the intensity of the signal required for this experiment would be much lower. This is because the energy of the wingbeat of insects is much lower. To compensate for this measure, the frequencies of sound signals from the mobile speaker were calibrated with the similar energy as produced by insects during their flight. The higher frequencies greater than 850 Hz were detected by the three microphones with at least 4m in the indoor environment. But this was not the case observed in outdoor environments. The same sinusoidal signals were not detected by the microphones greater than 1m. The reason behind this is the presence of environmental noise that reduces the intensity of the signal as distance increases, thereby reducing the effectiveness of microphones to detect these signals. Despite the frequency response of these microphones being between 20 Hz and 20 kHz, these microphones were not able to detect the sound signals with frequencies less than 150 Hz. This was the result observed on detecting the maximum range of microphones for a low-intensity signal which determines the use of this technology in insect monitoring applications.

What is the performance of the suitable sensor technology?

During these experiments, the insects were only monitored when they approach close to sensors within 15cm from it. The insects were not caged nor placed in a position at a certain distance from the sensors. Since the presence of insects in outdoor environments would be rare (as the assurance of insects present near the sensor is not straightforward), a UV lamp was used to attract the insects near the light based on the vacuum cleaner effect. This relatively observed over 150 insects in the duration of the testing in three different environments.

Now, we will discuss the performance of insect detection in outdoor environments using acoustic sensors. From the Table 6.1, it is observed that the recall rate of 84% in detecting insects using acoustics is better in suburban environments. It is mainly due to the less amount of noise present in the surroundings. The impact of noise present in the environments had led to an average recall rate of 76% in urban environments. In the experimental site at Artis Zoo, the noise profile was highest in comparison to the other two environments. As a result, a very low recall rate of 58% was observed. The precision on the performance of the system was observed to be 35% in suburban, 12% in urban and 4.4% in Artis Zoo experimental site. This poor performance in precision is observed mainly due to the noise in the environment and the hard threshold that we have used in our insect detection algorithm. The reduction of noise in the environment ultimately subdues the sound produced by the insects, which eventually results in an extremely poor recall rate. Similarly, the same effect was observed while using the pop filter on the microphones. This nylon material did have a reduction of wind noise, but at the cost of microphones hearing the insects' sound as well. As the pop filter, filters out the insects, this technique will not be ideal for insect monitoring applications. Thus, these results prove the fact that the increase in the external noise does affect the performance of the system in detecting airborne insects using microphones.

The effect of multiple insects near the microphones will have different insights which will be discussed as follows:

- If two distinct species of insects are observed with ideally differing wingbeat frequencies, the determination of both insects are made. Although they cannot be separated by species from our experiments, the detection of these insects may be very well recognized by multiple peaks at different frequencies.

- If the two insects of the same species fly across at the same distance from the microphone and beat their wings, two possibilities can be observed. If these two insects ideally beat their wings in the same time period, the frequency of their wingbeats is in phase to each other. The energy of these two insects is almost doubled and depicted as a single insect. This effect in sound signal is known as constructive interference. If these two insects ideally beat their wings in time shift, the frequency of their wingbeats are can also be observed opposite in phase. This results in nullifying the energies by these two insects leading to the non-detection of these two insects at that time. This effect in sound signal is known as destructive interference.

When the insects fly closer to the microphones, the energy will be high and it becomes easier for the microphones to pick up these sounds. Whereas, an increasing distance would drastically drop the energy observed due to the wingbeats. This will eventually impair the ability of this technology to detect the wingbeats of insects at varying distances. However, the sound produced by insects such as courtship songs can be very well detected by the microphones at a distance up to 10 meters based on the intensity of the sound produced by the insects.

What are the ways to identify the airborne insects using the suitable technology?

Classification is a procedure to categorize and determine insects at various taxonomical levels. The act of classifying is performed using classifiers. The are various methods and classifier techniques[15][16][17][18] that we have discussed in the Chapter 3. But to make a classifier work, there must be an adequate amount of insect data which is also known as training data. The extracted feature vector is transformed and used as an input to the classifier which determines the output based on trained data. The classification procedure starts from the literature study of insects in Section 2.1. The airborne insects, by theory[39], can be classified up to the third level of the taxonomy chart. As all insects are organisms that have multiple cells, these are placed in the animal group in the kingdom. Insects consist of an exoskeleton for their body support instead of a backbone and they have segments in their body with joint pair of appendages, insects are known as invertebrates which comes under Arthropods phyla. As the insects have six legs, they come under the class Insecta. As we are dealing with airborne insects, the types of insects with wings are placed in Pterygota sub-class[40]. Beyond this level, we need to know the ideal feature of insects to categorize them in order, family, genre and species level in the taxonomy chart. These features of insects include but are not limited to wingbeat frequency, wing movement pattern, shape, size and colour. As we use acoustic sensors, we have sound data that can be used to detect and extract the wingbeat sounds produced by the insects. By virtue of this, we can extract the wingbeat frequency of insects which can help us to categorize insects. The wingbeat frequencies of insects vary from 10 Hz for larger insects such as butterflies to 1200 Hz for smaller insects such as mosquitoes and houseflies. Identification of certain wingbeat frequencies range can help us to categorize them in order or family level and sometimes up to species level. But there is an uncertainty to classify the insects only based on their wingbeat frequency. As there are a lot of flying insects species found in the ecosystem whose wingbeat frequency only range between 10 Hz and 1200 Hz[31], there is a large possibility of overlap in wingbeat frequencies within certain species. Thus, it becomes important to extract some features of flying insects that would increase the probability to classify insects based on species level. As we extract the wingbeat frequency from the audio signal, we can estimate the size of the insects. Similarly, we can also extract the wing pattern from the insects that were observed during their flight. These wing patterns are unique signatures of the insects. These three features extracted from the audio signal during the insect movement will help us to improve the classification of insects technique down to species level.

7.2 Effect on the parameters

Effect of window size

Increasing or decreasing the window size may affect the performance of the system in detecting the occurrences of insects. This depends on the number of times the same insect appear again within the time window. If the window size is halved, the performance of the system is almost similar to that window size of 1 second. This is because the same insects had not appeared again within a 0.5-second time frame and hence, the performance was found to be similar. Whereas, doubling the window size had led to a decrease in recall rate by 17%, 19% and 24% for urban, suburban and Artis zoo experimental sites respectively. This is mainly due to the fact that some insects that appeared within this time frame have been not detected by the algorithm by reducing the number of true positives and thereby decreasing the performance of the overall system.

Effect of environmental conditions

The environmental conditions do have an effect on both the insects and the recording data of microphones. As the wind speed observed to be moderate during the conduction of experiments, these must not have a significant effect on the flight of insects. The wind speed observed during the experiment will however alter the microphone recordings by providing more noise. This will hinder the performance in the detection of insects observed during that time. On contrary, the environmental factors such the temperature and humidity do not alter the performance of microphone recordings.

Effect of size of insects

The size of insects determines the wingbeat frequency of a particular insect[31]. The wingbeat frequency of an insect is inversely proportional to the size of the insect[31]. The smaller the size, the larger will be the wingbeat frequency. As the size of the insect increases, their wingbeat frequency drops substantially. The relative size of insects measured from the wingbeat frequency of insects may also be used as a feature to classify the insect species. The size of insects has effects on the detection of their flight sounds detected by the microphones. The smaller insects such as mosquitoes, houseflies, and moths have good accuracy in detection compared to the larger sized insects such as bumblebees, butterflies, dragonflies and much more. The assumption of this notion is mainly due to the wingbeat frequency of insects. The wingbeat frequency of insects that is less than 150 Hz is difficult to be heard by the microphone in the outdoor environments as we have discussed earlier in Section 6.1. Despite the frequency response range of the microphones being from 20 Hz - 20 kHz, the ability of the microphones to hear wingbeat sounds produced by these large insects is quite difficult.

7.3 Conclusion

In this thesis, acoustic sensors technology was used to detect and monitor airborne insects in outdoor environments; namely in urban and suburban areas. The condenser and MEMS microphones were used to detect and monitor these airborne insects. From the results of the range detection experiment, we can infer that the performance of MEMS microphone is outperformed by condenser microphones. The performance of the microphone in detecting the airborne insects had led to a recall rate of 76%, 84% and 58% in urban, suburban and Artis Zoo experimental sites respectively. Although a good recall rate was observed, the precision of the system in these environments was very low because of the noise present in the environment and the hard threshold used in the insect detection algorithm. The precision of the urban, suburban and Artis Zoo experimental sites was observed to be 12%, 35% and 4.4% respectively. The performance of the microphones can also be improved by addressing the methods suggested in Section 7.4. Although the maximum detectable range of microphones is less compared to other sensor technologies, acoustic sensors do not use artificial lights nor harm insects in any way. This enables us to monitor the insect species without creating an imbalance in the ecosystem. Additionally, the results of the research lead to the direction of implementing acoustics sensors in insect monitoring applications.

7.4 Future works

- The collected insect data through microphones in this research can be processed further to classify them using machine learning techniques. The insect detection using peaks in this system can be extended by applying a binary classification. It will increase the probability in segregating the insect and non-insect sounds. This ultimately allows us to process the more restricted and required data for identification of species.

- The extracted features of insects can be used as a data for insect classification. There are many classification technique as discussed in Section 2.2 that can be used to determine the order, family, genre and species of insects. This will really emphasize the importance of detecting and classifying insect species using acoustic sensors.

- The performance matrix can be calculated on multiple classifiers to detect the insect species using their wingbeat sounds. This experiment will enable to select the optimal classifier in detecting insects using their wingbeat sounds. Later, the algorithm of classifier can be used to improve the computational complexity involved in process which will help us to save time.

- Multiple microphone devices can be employed in an array and effect of phase shift can be used to determine the speed of insects, which can be an additional feature for insect classification.

- As the raw recording of experiments is a mixture of source signals and noise, the individual components can be analysed through the Blind Source Separation technique[41]. This technique can be used on a model through unsupervised Mixture Invariant Training[42]. The raw mixture of data is given as an input for training to determine the information regarding the individual source components. This technique can be widely used when two or more insects are observed at a time and try to extract the features of multiple insects individually.

- An embedded product can be designed with a combination of various sensors. This device will include data from multiple sensors which will help us to gather and extract more properties of insects. As the set of data from a particular species increases, the probability of classifying them with higher accuracy can be observed. Additionally, this device can be deployed in remote places with minimal requirement of human supervision.

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