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Designing a small and low-energy wild life tag for parakeets within an urban environment capable of tracking and online activity recognition

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Abstract

This work is concerned with designing and building an online activity classifier and tracking device on an embedded system to monitor parakeets. This involves the design choices in localization, feature selection, classifying algorithm and optimization of required features and algorithm parameters. In order to reduce the number of inputs to a machine learning algorithm, Forward Selection was applied, which reduced the number of features from 20 to 7. The resulting feature sets were then applied to six learning algorithms; k-Nearest Neighbours, Naive Bayes, Neural Network, Linear Discriminant Analysis, Decision Tree, and Support Vector Machine. In order to evaluate the machine learning algorithm, data from a parakeet was used for training and testing using a 70% to 30% ratio, creating a generic classifier which could accurately recognise the activity of a parakeet. The models were evaluated and compared according to three main metrics, namely performance, battery usage, and ease of implementation, as well as other metrics such as variance in performance, usability and training effort.

It was found that the combination of the decision tree classifier with seven time-domain features from the accelerometer's 3D vector magnitude comprised the best compromise between the evaluated metrics. The decision tree parameters were tuned such that its performance could be maintained while minimizing the tree size. A window size of two seconds and a 50% window overlap was used to yield an excellent compromise between computation and performance. The accuracy of classification varied between 87 and 90%.

Next, satellite-, ground-based- and radar tracking methods were compared in terms of energy consumption and accuracy. A localization system has been proposed based on the received signal strength of Bluetooth Low Energy beacons. These beacons were detectable from a 40-meter distance.

Finally, this tracking device and online activity classifier have been implemented on the AKMW-iB001M beacon, and the performance will be tested in the future on wild parakeets in Málaga, Spain.

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List of acronyms

AAR Animal Activity Recognition

AoA Angle of Arrival

BLE Bluetooth Low Energy

CPU Central Processing Unit

DSC Doppler Shift Calculations

DT Decision Tree

FN False Negative

FP False Positive

GPS Global Positioning System

GSM Global System for Mobile Communications

ISS International Space Station

k-NN k-Nearest Neighbours

LDA Linear Discriminant Analysis

LZO Lempel-Ziv-Oberhumer

LZW Lempel-Ziv-Welch

NB Naive Bayes

NN Neural Network

RAM Random Access Memory

RSS Received Signal Strength

SVM Support Vector Machine

TDoA Time Difference of Arrival

ToF Time of Flight

UHF Ultra High Frequency

VHF Very High Frequency

Chapter 1

Introduction

Animal behaviours and activities are essential to better understand the species and their environment [1], [2]. For example, social scientists are turning to animal behaviour as a framework in which to interpret human society and its problems [3]. Many problems in human society are often related to the interaction of environment and behaviour or genetics and behaviour. Another example is that of Sir Charles Sherrington [4]. He developed a model for the structure and function of the nervous system based on close behavioural observation of animals. Other research showed that animal behaviour could tell about the animals' health [5] and their social interactions [1]. Activity recognition might also be implemented to protect animals from poachers [6]. Finally, the behaviour and activities of animals often provide early warning signs of environmental degradation. Changes in sexual and other behaviour occur much sooner at lower levels of environmental disruption than changes in reproductive outcomes and population size [7].

Therefore, many scientists collect data on these behaviours and activities on ways varying from making notes with pen and paper to using collars with sensors. One of the oldest techniques is to observe the animal by human observers over a long time [8]–[11]. An issue with this technique is the human-dependency, which requires an observer to be present at all times to monitor the animals' activity. Human observation is not only tricky but also impractical, especially when such an animal moves to locations restricted to humans or travels with high speed. Another issue is that the animal might behave differently in the presence of a human (which primarily is the case for wild animals). Another observation technique is to observe via cameras. This eliminates the problem of a human observer needing to be present at all times and causes no influence on the behaviour and activity of the animal. The animal can be filmed, and later its behaviour and activities can be classified. However, with cameras, one is bounded to a fixed area and can therefore only be used on animals in captivity or restricted to a space. Finally, collars can be used to collect information on the behaviours and activities of animals. With this, a small device is secured onto the animal with various sensors attached to it. These sensors gather various kind of data (e.g. movement, location, temperature) about the animal. The animal always carries the collar along, providing more information than human observations and cameras.

Sensors in the collar gather a large amount of data. To interpret this sensor data into animal behaviours and activities, one uses machine learning. Machine learning looks for patterns in the data symbolizing certain activities (e.g. *walking, standing, flying, swimming*). This classification is often performed offline, after retrieval of the sensor data. Retrieval of the data is done either via removing the sensor or transmitting the raw data wireless for offline analysis. Wireless transmission is costly in terms of energy. Therefore, processing sensor data on an embedded system can be cheaper in terms of energy demand instead of sending the raw data over a radio. Many applications would benefit from live updates regarding an animals activity, for instance, to notice environmental disasters, such as forest fires.

Animal Activity Recognition (AAR) is achieved by processing sensor data on a device on the animal. Subsequently, the activities periodically transmit the animals' behaviours and activities. Therefore, the embedded device needs to compute and classify the gathered data continuously. These devices are limited in terms of storage, power and computational resources. This poses the challenge to design a sophisticated learning algorithm on a non-intrusive and low-energy system.

Another way to get insight into the behaviour of animals is location tracking. Location tracking supports tackling the many environmental challenges we currently face, including problems posed by invasive species [12], [13], the spread of zoonotic diseases [14] and declines in wildlife populations due to anthropogenic climate and land-use changes [15].

To track an animals location, one has to account for the required power as well as the needed localization infrastructure. Almost every tracking technique consists of connecting to a reference point to determine its location. The farther away from this reference point, the more energy it costs to connect, but also one can measure on a broader range. To measure the same area with low power reference points requires more reference points. Tracking is accomplished through four main techniques: human tracking, satellite tracking, local tracking and radar tracking. Human tracking works by marking the animal and when seen again writing down the marking and location. This method results in a very sparse dataset. Satellite tracking can accurately track locations to 5 m precise. However, connecting to a satellite requires much power. Local tracking requires less power than satellite tracking, but more tracking points need to be included. Finally, radar tracking has all the tracking points already in place, but it can not track single targets. The challenge is to balance the tracking infrastructure and energy consumption.

1.1 Target animals

Worldwide, there are about 350 species of parrots and parakeets (order: Psittaciformes). In total, 54 of these species have been introduced to areas outside their native ranges, and 38 species have become established in the non-native range [16]. Humans exhibit ambivalent feelings toward parrots and parakeets. Many of these birds are strikingly beautiful and highly prized as companion animals, while others are banned because of potential agricultural damage or competition with native species. Many parrot species are afforded special protection because they are endangered in their native habitats. Often these species are considered crop pests and persecuted by farmers [17].

The monk parakeet (Myiopsitta monachus) and rose-ringed parakeet (Psittacula krameri) are undoubtedly the worlds most successfully introduced parrot species. Each species now enjoys a broad non-native range where conflicts with human activity include crop damage [18], competition with native species [12], [13], and property damage [19]. Each species exemplifies invasiveness through its capacity to adapt to new conditions and to exploit opportunities created by human activity. Biologists and resource managers are challenged to develop and implement effective strategies that not only protect resources from these invasive species but also account for public opinions, which often favour the charismatic avian invaders.

Eliminating small populations of these birds is the primary strategy to deal with their immense growing population. The main problem with dealing with these parakeets is the lack of information on the birds. While there have been previous studies into the monk parakeet and rose-ringed parakeet, they are either outdated [20]–[22], or only look at global patterns [12], [23] or are observatory studies [8]–[11] leaving space for human error.

Currently, the University of Málaga is trapping monk parakeets and tying neck-collars around the birds (see Figure 1.1). By marking these birds, they get certain primitive information. However, observatory studies do not supply enough information. To get a better understanding of the monk parakeets' location, behaviour and activities need to be analysed.

To track the location and online classify activities, a data logger is used. A data logger is a small embedded device with multiple sensors (e.g. movement-, pressure-, heat- and location-sensors). This logger gives detailed information on the bird and can be used as an insight into the life of the birds. Loggers are also able to measure at locations restricted to humans, due to natural obstacles. Finally, they can measure for long periods, sketching a better image of the activity of the bird. Since no parakeet specific logger is yet available, we will focus on designing such a logger.

Figure 1.1: A parakeet with a neck-collar

The main body of this thesis deals with the different design aspects of such an AAR system. This includes the choice of hardware, infrastructure and the activity recognition. Finally, a prototype of the system is built and evaluated.

1.2 Research question

Within this study, we answer the following research question:
What level of online activity recognition performance can be achieved for birds while tracking locations in urban environments?
Sub questions include:

- *How can a bird activity recognition system be implemented on a small, light-weight and low-power embedded device?*
- *What are the trade-offs between accuracy and functionality against weight and energy?*
- *How to minimize the required localization infrastructure?*

1.3 Report organization

The remainder of this report is organized as follows. Chapter 2 gives a state-of-the-art wildlife tag. Within Chapter 3, we will sketch the hardware requirements and explain our choice of hardware. Next Chapter 4 shows the used methods. Chapter 5 shows the results of the implemented tag. Finally, within Chapter 6, these results will be discussed, and a conclusion is drawn. Also, recommendations for further development and research are given in this final chapter.

Chapter 2

State Of The Art

This chapter discusses the state-of-the-art of data loggers and the used techniques of those loggers. We divide the state-of-the-art section in location tracking, data preprocessing and behaviour classification.

2.1 Techniques

2.1.1 Location Tracking

Within this part, we classify tracking systems (see figure 2.1) in the way they derive location data: 1) satellite tracking, 2) local tracking, 3) radar tracking. All techniques and specifications are further elaborated by Bridge et al. [24].

First, we look at satellite tracking, which is suitable for real-time tracking, but very costly in terms of power and money. One can do animal tracking through the Global Positioning System (GPS) [25]–[27] or through the Doppler Shift Calculations (DSC) [28], [29]. While GPS is very accurate (accuracy at 5m vs 100m-50km compared to DSC), it also uses much power and therefore needs a bigger battery. The smallest GPS tags at present are in the 20 to 150-gram range, which limits their application to larger animals ($> 200g$). Another difference when comparing GPS to DSC is the number of fixes per day. DSC is only able to do this once a day, while GPS can get multiple fixes throughout the day. Therefore, DSC is unfit for tracking small movement but great for migratory movement.

When choosing for GPS, there is a difference among a cold start, warm start and a hot start [30]. At a cold start, the GPS does not know where on earth it is located and has no clear idea where the satellites are. Therefore, the GPS locates a satellite to connect to so it can get a general impression of its location. When connected to a satellite, it will request the almanac, which contains the approximate information on all the other satellites locations. In total, the time to get a fix from the start-up is about 15 minutes. Next, we have a warm start; with this, the GPS already has the correct

Type of start	Requirements	Time To Fix
Cold	-	15 minutes
Warm	Correct almanac Within 100 km of previous known location	45 seconds
Hot	Location known within last 2 hours Ephemeris data of 5 or more satellites	22 seconds

Table 2.1: Different types of GPS start-ups

almanac data and a previous location within 100 km of the current location. Then it asks the ephemeris data from the satellite which contains that satellite's detailed orbital information. The time to get the first fix with a warm start is only 45 seconds. Finally, there is a hot start. With this, a position was determined within the previous 2 hours, and the GPS has the ephemeris data of at least five satellites. Now time to a first fix takes about 22 seconds. Table 2.1 gives an overview of these three types.

Using local tracking gives some options which require less power than GPS. Here we can use tower identification, Bluetooth and Wi-Fi identification, radio telemetry, acoustic telemetry, magneto-inductive tracking, dead-reckoning and solar geolocating. Tower identification (or radio-tracking) [31] is the most straightforward tracking system since one only needs to identify with which tower the tag is connected. However, this is not always doable due to coverage issues and support of mobile companies. Detailed movement can not be tracked this way since these towers cover a large area. On the other hand, it works well in urban areas, which are always covered. Another option is the use of Bluetooth [32], [33] or Wi-Fi [34]. By measuring the received signal strength of different beacons, one can determine where a device is located. Bluetooth is a better option for bird tracking since it requires less power than Wi-Fi. How detailed a location can be tracked depends on the amount of Bluetooth tags spread out through the area. Therefore, the main issue is that it can only be used in a predetermined area. However, the technique excels in individual movement tracking.

All currently mentioned techniques use various methods to determine the exact location. First of all, merely node/tower identification can be performed. This is the easiest method and gives a range of the radius of the node, without adding an angular measurement. This method is power inexpensive since the tag only needs to listen if a node is nearby to know where it is. On the other hand, it gives a grainy resolution of the animals' path. Next, Time of Flight (ToF) [35] can be used to determine the exact distance from the node. It is computed through a known velocity of the signal, given that the node's and tags clock are synchronous. This computation results in a known position circle. When a third node is added, one can pinpoint to the exact position, by overlapping the position circles. The disadvantage of ToF is that it is very susceptible to multipath fading. Also, the tag needs to send out a signal and then download each position circle, making it power expensive. A similar technique called Time Difference of Arrival (TDoA) [35] is mainly used in GPS. The tag measures the difference in time of arrival between two or more signals. By using this data, the tag can calculate its position relative to the signal sources. The location of the signal sources needs to be known in order for this to work. One of the major disadvantages in this technique is jitter, a small variation in the frequency of the output signal. While the tag does not need to send out any signal, these computations itself can be power expensive. Another technique is to use the Received Signal Strength (RSS)/fingerprinting [36]. This technique knows each RSS on any location. By comparing the RSS to the known 'map', one can determine its location. This technique is mainly used indoors since each location needs to be measured beforehand. It is also possible without such a 'map' by computing the distance through the RSS and loss. Like ToF, this makes it susceptible to multi-path fading and adds extra computations. Finally, Angle of Arrival (AoA) [35] can be used to calculate the angle of incidence of an incoming signal with respect to a reference. This method is mainly used in DSC. It calculates position in one of two ways. In the first method, the AoA and ToF information is combined, resulting in the position of the tag in polar coordinates. The main advantage is that only one node is necessary to determine the location, but has the same disadvantages as ToF. The other way two or more AoA stations are set up at known distances from each other, the AoA of an incoming signal is calculated at each station, and the position of the tag is calculated through triangulation. The advantage here is the lack of time components, using angles only leaving space for jitter and a-synchronization. The disadvantage is that the AoA stations must have a fixed reference for the calculated angles to have any meaning, limiting the measurable area.

To continue on local tracking, we have radio telemetry [37], which uses Very High Frequency (VHF) or Ultra High Frequency (UHF) antennas and transmitters. The simplest VHF transmitters emit pulses of energy at a particular radio-wave frequency. Multiple tags can be tracked in the same area by using different frequencies and pulse patterns. Generally, a limited number of receivers are used in a given project, and a receiver must be within a few kilometres of a transmitter, depending on the equipment and the environment, to detect it. Therefore, these systems are not capable of tracking migratory animals over long distances unless someone expends the tremendous effort to follow an animal with a mobile antenna. In situations where radio telemetry is not practical or appropriate (due to, for instance, the saltwater) one can use acoustic transmitters and receivers to track wildlife [38]–[40]. Again these systems can only track a limited number of receivers within one kilometre and are mainly used below water. When looking at underground tracking

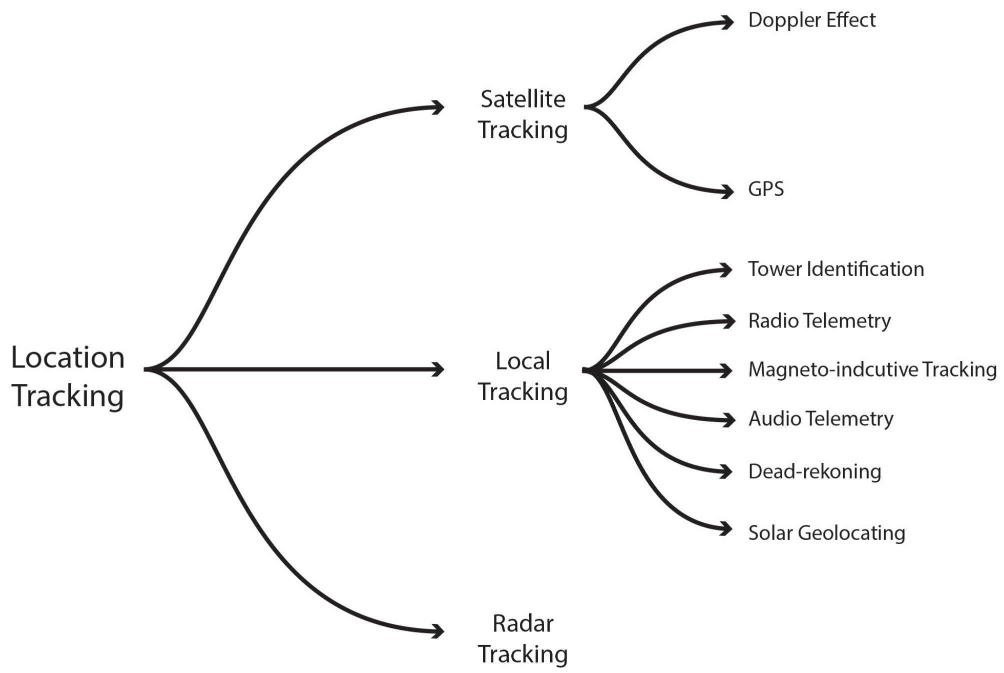

Figure 2.1: Tracking system classification

systems, there is only one active tracking system, called magneto-inductive tracking [41]. Localization of mobile devices underground is exceptionally challenging, with radio propagation severely attenuated by soil and moisture. Therefore, magnetic fields are placed above grounds which penetrate the ground, and these strengths are recorded and sent when the animal is above ground. A more passive tracking option is dead-reckoning [42]. Dead-reckoning uses a known start position and derives the new positions through the use of the animals' speed, heading and change in height with respect to the previous positions. This system does not require a lot of battery power and can, therefore, work over a long time. Due to a variable (wind) speed or drift the errors in position are very high [43]. A solution for this could be to make an independent fix through GPS at regular intervals. However, this would bring back the weight problem. Finally, we have a solar geolocator [44], which tracks its latitude through the length of the day and longitude through the time of solar noon. This is again a cheap and small system, which does not require a lot of battery power. However, the accuracy can range from 50km to 200km, and it can only locate a bird once per day, making it inadequate for tracking local movement.

The final option is radar tracking [45]. Radar tracking has some distinct advantage. For instance, the radar hardware and infrastructure are already in place and is maintained. Furthermore, many software packages exist for accessing and visualizing both real-time and archived radar data. Next, it can even track the smallest animals like insects. Finally, no additional tags need to be present on the animal itself. However, radar tracking also has its limitations. They are more suited to track masses than individuals, and the radar is bound to a particular area. Also, no other information can be derived than an animals location. Furthermore, the current infrastructure is mainly focussed on aerial species, while there are certainly options for maritime species.

2.1.2 Data preprocessing

Current sensing technology has enabled to monitor animal behaviour and activities with the help of accelerometers [25], [26], [38], [46]–[49], cameras [38], [50], microphones [38]–[40], thermal sensors [48], barometers [51] and EEGs [46] among others.

With all this sensor information, one can identify different behaviours. This identification is accomplished by manually comparing their behaviour with the data, which is feasible for a limited dataset and behaviours; as done by Bouten et al. [25] and Sheppard et al. [49]. However, with large sets of data, it is easier to do this through machine learning. We will elaborate on this in the next section.

When tracking an animals location and behaviour, much data is generated. To deal with this, either a large memory is needed, some data processing needs to be applied, or frequent transmissions need to take place. A good option would be to include a large memory if no form of transmission is used, making the total tag power efficient. However, if no recapturing of the animal for data recollection is necessary, forms of data processing or data compression need to be used.

The simplest data processing technique is to take the mean of values over a period (windowing) and not send all raw values. A much-used technique is to calculate the 3D-vector and its features over a small time window (1-2 seconds). These time and frequency-domain features are typically used in activity recognition [24], [25], [41], [48], [49], [52]. Another idea is to cut down on the sampling frequency. For instance, Nathan et al. [53] sample their accelerometers for durations of 16.2 seconds at 10-minute intervals. This sampling technique gives a grainy resolution, but a high resolution is not always necessary. Finally, one can already compute the necessary data for the research locally. Again Nathan et al. calculate 'roost arrival time', 'daily travelled distance', 'maximal displacement' and 'flight straightness' locally and only stores and transmits these values.

To make algorithms less complicated, one can perform feature reduction. Available techniques are dimensionality reduction or feature selection (also see figure 2.2). Dimensionality reduction uses a statistical procedure to reduce features which might be redundant [54]. It orthogonally transforms the set of features into princi-

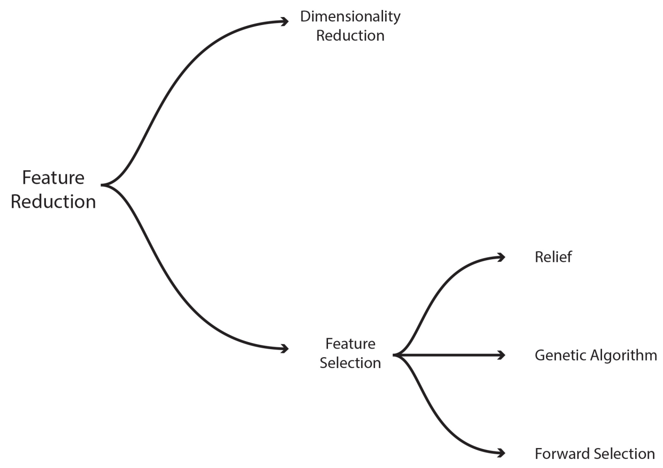

Figure 2.2: Overview of feature reduction techniques

pal components, which are sets of linearly uncorrelated values with a covariance of 0. Then these components are ranked by their variance. Dimensionality reduction can be useful when working with many features from the same domain to filter out duplicate features. Feature selection can be done through relief [55], genetic algorithms [56] or forward selection [57], all different methods which choose features which contribute the most towards classification accuracy. Relief estimates the quality and relevance of features by their ability to classify and discriminate between similar classes. Relief is excellent to predetermine the used features. Next, genetic algorithms choose a random amount of features and see which features score the highest in terms of classification performance. The higher features are retained for the next generation until an optimum is found. The main problem might be that one can reach a local optimum. Finally, forward selection selects features one by one and evaluates their performance according to a classifier. Again the highest performing features are added to the selection. However, here the problem might be that discarded features cannot be re-selected, thus again only reaching a local optimum. Bisby [58] compares these techniques on accuracy and execution time. She shows that forward selection results in the lowest execution time while still retaining accurate accuracy.

Another idea to deal with large datasets is to compress the raw data. The standard technique is gzip (LZ77), which is a dictionary coder. It works well but is also more battery expensive than Lempel-Ziv-Oberhumer (LZO) and Lempel-Ziv-Welch (LZW) [59]. LZO and LZW are specially developed for energy-constrained devices and are also dictionary coders. However, due to the complexity of these algorithms, we will not further investigate those.

2.1.3 Classification Algorithms

In section 2.1.2, we looked at different sensors, feature selection and data compression. The next step is to classify the animals' activity through a machine learning algorithm. First, we will discuss all relevant algorithms, including the AAR that use these algorithms. Then we show relevant research comparing or evaluating these algorithms. The most used algorithms are k-Nearest Neighbours (k-NN), Naive Bayes (NB), Decision Tree (DT), Neural Network (NN), Support Vector Machine (SVM) and Linear Discriminant Analysis (LDA).

k-NN searches the training data points to find k data points closest to an incoming data point in order to predict it. These k training examples are called the k "nearest neighbours" of the incoming data point. k-NN is easy to implement for multi-class problems, requires no training step and uses instance-based learning. The constraints of the algorithm are that it is a slow algorithm (especially as datasets grow), does not perform well on imbalanced data and is very sensitive to outliers. Bidder et al. [60] tests k-NN in AAR for badgers, camels, cormorants, dingos, kangaroos, wombats and humans. While they reach high accuracy for kangaroos and humans (91% and 95% respectively), the average accuracy lays at 78%. The two aerial species, cormorant and wombat, reach an accuracy of 77% and 76% respectively, showing worse results than the average performance.

NB builds a simplistic probability model which assumes that features are independent and evaluates them independently. It also works well in multi-class problems; it is easy to understand and can work on any size dataset. The cons are the assumption of independence class features (which is never the case in real life), and the algorithm suffers from *Zero Frequency* [61]. Browning et al. [62] use NB to determine whether the location of diving behaviour can be predicted from GPS data across three seabird species. NB predicted only non-dives well (85-95% accuracy), but did poorly on predicting dives with only 40% accuracy. The author claims this due to the unbalanced data set.

DT builds a tree structure with nodes. At each node, the values of the features are compared in order to choose which branch to take. At the final branch, a class is selected. It is a "white box" in the sense that the acquired knowledge can be expressed in a readable form. Next, the number of hyper-parameters to be tuned is almost null. Drawbacks include the high probability of overfitting, and the tree can become complicated when there are many labels. AAR has been done on sheeps [63], [64] and cows [65]–[67] with DT. Each research reaches accuracies around 90%, also performing well with real-time classification.

NN replicates a network containing layers, in which several nodes are connected with each neuron on the preceding and succeeding layer. Each connection has a defined weight on which the feature is multiplied with, leading to a final classification result. The algorithm outperforms almost every other machine learning algorithm and is widely used in the offline machine learning. However, NN requires more training data than other machine learning algorithms, acts as a black box and is computationally expensive. While we can find many types of research comparing NN to other algorithms [53], [68], [69], no implemented versions are presented up to now.

SVM aims to maximise the margin between training patterns and the decision boundary and drawing hyperplanes between classes. SVM focusses on data points which are from different classes but are close together, in comparison to other algorithms which focus on all data points. The algorithm is useful in the higher dimension, when classes are separable and when the number of features is higher than the training examples. However, it is difficult to find the appropriate hyperparameters and kernel function and does not perform well in case of overlapped classes. Goa et al. [70] build a web-based tagging and AAR system. They train an SVM through data from humans, dogs and badgers all with an accuracy of over 90%. Lee et al. [71] show an implemented version of an SVM to measure aggression of pigs, with an accuracy of 95,2%.

LDA expresses one dependent feature as a linear combination of other independent features, forming a set of continuous independent features which define class labels, aiming to distinguish between independent and dependent features. The algorithm works well if the class conditional densities of clusters are approximately normal, also when there are more features than training examples. LDA fails to find the lower-dimensional space if the dimensions are much higher than the number of samples in the data matrix. Next, it also suffers from to discriminate between non-linearly separable classes. Also, Viazzi et al. look into pig aggression, classifying with an LDA with 89% accuracy. This version is no implemented version as presented by Lee et al..

Kamminga et al. [69] compare seven different machine learning algorithms for their behaviour classification. They look at memory usage, Central Processing Unit (CPU) execution time, accuracy and F-scores. It shows that the NB algorithm is the cheapest to use in terms of resource usage, closely followed by DT, NN and Deep Neural Networks. Bisby [58] shows the same results but also includes an implemented version of the DT algorithm.

Nathan et al. [53] also compare the Random Forest algorithm to the previously mentioned algorithms. However, they do not look at resource usage, which is excepted to be higher than DT, since it is the outcome of multiple DTs.

Chapter 3

Hardware selection

Within this chapter, we will sketch the requirements for a wildlife tag and explain what hardware fulfils these requirements.

3.1 Requirements

When measuring on animals, ethical rules apply to protect the animal. The foremost rule is the maximum weight that may be added to the animal. For birds, this is 5% of the total weight. Since parakeets weigh around 150 gram, our tag can weigh 7,5 gram at maximum.

To get an overview of the daily activities of the parakeet, we want to log its location and real-time classify its activities. The importance of these parameters are explained in chapter 1. Next, to get a better overview of these activities, we want to see if specific patterns emerge. With a month worth of data, we believe to have enough data to get a better insight into the behaviour of the parakeet.

Finally, the parakeet is returning to its nest each night, but to capture them is quite tricky. To decrease the chance of data loss, we want to download the data from a distance, instead of trying to recapture the bird for tag retrieval.

For the tag to be used on rose-ringed and monk parakeets the following requirements apply:

- The tag must weigh 7,5g at maximum.
- The tag should operate for at least one month.
- Data should be downloadable from a distance (no tag retrieval).
- The tag should be able to log its location.
- The tag should be able to real-time classify the activity from the animal.

3.2 Transmission

The gathered raw accelerometer data needs to be recovered from the device. There are two main options with each having its implementations again. The options are satellite systems and ground-based receivers.

The first option is the use of satellite systems. These systems can update real-time and send their data over a satellite link. This option gives an up-to-date overview of each tracked individual. However, as can be imagined, these systems have high costs and power requirements. An existing application which uses a satellite system is the ICARUS initiative [72]. The ICARUS initiative is a tag connected to a module on the International Space Station (ISS), mainly focussed on bio-logging. The main difference between conventional satellite systems is that the ISS is closer to the earth and thus needs less power to communicate.

The other option is the use of ground-based receivers. These are less power expensive than satellite systems but do allow downloading the data real-time. The only issue might be coverage since not all networks are available at every place, especially in maritime areas. The most common transmitter is the Global System for Mobile Communications (GSM) transmitter since the GSM network is available worldwide. Next, we have radio telemetry as described in section 2.1.1. Radio telemetry can only be used when the transmitter is in the neighbourhood and can not handle a large number of data transmissions. Finally, there are other long-range transmission protocols like Amber Wireless, Ingenu, LoRa, NWave, Platanus and Sigfox as described by Baharudin and Yan [73]. These ground-based receivers fit well into our wanted application since they are power efficient and do not require tag retrieval.

To circumvent transmission altogether, one can also do tag retrieval. With this technique, tags only store the gathered information. After some time the animal must be recaptured so the tag can be recovered and data can be downloaded. Overall this is an alternative method for wireless monitoring. This technique is suited for homebound animals or when using a recovery beacon. This is not very well suited for parakeets since it is hard to catch them.

3.3 Power supply

The whole tag needs to be powered. The ideal situation would be to add a big battery so the tag can be powered throughout the whole year with a high sampling frequency. However, this is not possible for every animal due to weight and size restrictions. Therefore we present different charging mechanisms to power the device. The most straightforward solutions are to either lower the sampling frequency

Source	Source power	Harvested power
Ambient light		
Indoor	0.1 mW/cm^2	10 µW/cm^2
Outdoor	100 mW/cm^2	10 mW/cm^2
Vibration/motion		
Human	0.5 m @ 1 Hz 1 m/s^2 @ 50 Hz	4 µW/cm^2
Industrial	1 m @ 5 Hz 10 m/s^2 @ 1 kHz	100 µW/cm^2
Thermal energy		
Human	20 mW/cm^2	30 µW/cm^2
Industrial	100 mW/cm^2	1–10 mW/cm^2
RF		
Cell phone	0.3 µW/cm^2	0.1 µW/cm^2

Figure 3.1: Characteristics of various energy sources available in the ambient and harvested power. [75, Table 2]

or shorten the time when measuring or use power-efficient algorithms. Next, Mitcheson et al. [74] classify charging methods into electromagnetic radiation (RF), thermal gradients, light and motion. All techniques can be found in Figure 3.1.

Ambient RF is the most underdeveloped technique and still struggles with delivering significant power levels. Thermoelectric generation works well but is much dependent on the direct change in temperature. Solar power has the highest power levels and is mainly used in bio-logging [25], [72], [76]. The two constraints for solar power are light availability, especially for animals living in darker parts of the world, and the price of solar cells. Finally, there is motion-based energy harvesting, which is less efficient than solar energy harvesting but is less dependent on external factors. All these techniques increase the lifetime of the tag, but also the complexity.

Two techniques are generally used for power, one being solar power and the other only using a battery. Other techniques can also be used depending on the bird. For instance, RF can be placed underneath the nest if one is tracking a homebound bird (such as the parakeet). Thermoelectric generation can be used by placing one element on the bird and the other element exposed to the wind/environment. However these last two techniques have problems delivering significant power levels.

3.4 Placement

With all hardware in place, the next question will be to look at the placement and attachment of the device. Different attachment methods used in bio-logging are:

- Neck collar

- Harness
- Epoxy glue
- Glue
- Suction cup
- Dorsal fin clamp
- Rubber cement
- Attached to antlers

Not every one of these methods is suited for every species in bio-logging.

Some attachment methods are meant to release within a specific time, while others need to stay in place until they can be retrieved. Concerning the first method, it is also essential that the device is biodegradable or has a beacon so it can be retrieved.

Placement is also crucial in influencing the behaviour of an animal. Such a tag is extra weight for an animal making it less aerodynamic and having a higher energy expenditure. Next, some places are not fit for a tag due to characteristic behaviour of a species, like diving or digging.

Placement is a significant issue with birds since it can influence its behaviour and foraging. Vandenabeele et al. [77] claim that for plunge-diving birds, the tag can be best placed on the lower back while for strictly flying birds, the middle back is the right spot. Other places like the head, tail or belly give too much drag or do not stay put when diving. What is not taken into account is the effect on the measurements when placing these devices. For instance, Rattenborg et al. [46] use electroencephalography (EEG), which can be best placed on the head of a bird. Also, an accelerometer records more detailed movement when placed closer to the head than the lower back, making it possible to identify different kinds of behaviour precisely.

3.5 Hardware versus weight

Volatile animals are hard to track due to their migrating process. Therefore, a lot of solutions exist in location tracking (see Section 2.1.1); however, weight restrictions make not all techniques suitable for each animal (see Figure 3.2). To clarify, dead-reckoning and solar geolocating belong to the geologgers category. Since our tag can maximally weigh 7,5g, only radar tracking, geologging or tracking with ground-based receivers is possible. Other techniques are possible but decrease the battery life quickly; hence, it is not viable.

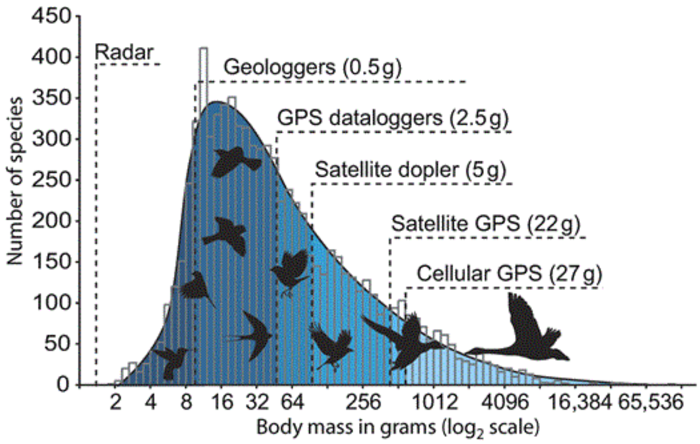

Figure 3.2: The frequency distribution of bird body masses (in grams) in relation to possible tracking technologies. Minimum bird sizes for each technology are represented according to the 5%-body-weight rule. [24, Figure 1]

3.6 Hardware selection

We used the AKMW-iB001M beacon from AnkhMaway (see Figure 3.3) since it fulfilled all requirements. The tag weighs 6g, falling in the 0-7,5g range. Through the 3-axis accelerometer, we can measure the displacement of the bird and use it to classify behaviour. The working time of the tag is 4.63 months based on a broadcasting rate of one second. Since we broadcast less but have more substantial computations, we suspect this will suffice for at least one month. Finally, it broadcasts with Bluetooth Low Energy (BLE) 4.0, which can be used to track location (as described in Section 2.1.1) and transmits its gathered data (as described in Section 3.2) from a distance. Moreover, the tracking will be discussed in Section 3.7. The full specifications of the tag can be found in Appendix A.1. No comparison was made with other tags.

The tag works well. It has a Bluetooth range of 50m, and the energy consumption of the accelerometer is very sparse. While it is difficult to use for attachment, it is light-weight. Finally, the tag is not perfect for development since no schematics are available.

While we used the AKMW-iB001M beacon for the development of our tag, we also used a logger to gather accelerometer data on parakeets simultaneously. This logger was the Axy-Trek sensor [78], which contained a GPS, 3-axis accelerometer, temperature sensor, pressure sensor and height sensor. The logger is able to measure for 5-6 hours after which the battery dies. Such a small battery life is sufficient for gathering data in a controlled environment. The sole purpose of this logger was to gather accelerometer data from parakeets; therefore, it does not suf-

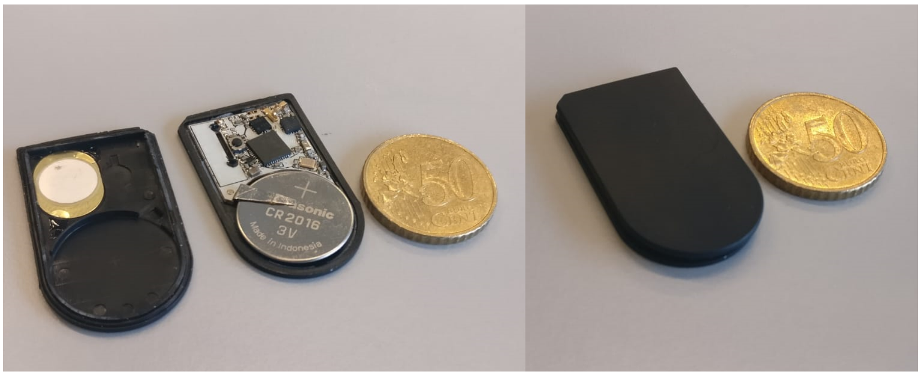

Figure 3.3: The AKMW-iB001M beacon open and closed respectively.

fice all requirements. For both tags, no schematics are available since both were commercially bought.

The Axy-Trek sensor was a perfect tag to do quick measurements. It had an easy to handle user interface and did not have any problematic initialization parts. Also, settings could be changed through the user interface, and rings were available for attachment. However, as stated before the battery life was poor (5-6 hours) and data could only be downloaded from the tag after capturing the bird, making it unsuited for wild parakeets.

For location tracking, we use standard MiniBeacons. It runs on two AA batteries and is easy to replace. Moreover, the precise working of location tracking can be found in the next section.

3.7 Location Tracking

We track location via Bluetooth identification (again, as described in Section 2.1.1). Bluetooth beacons (as described in Section 3.6) send out an advertisement signal. This signal broadcasts that they are there. The tag will pick up this signal and add it to its log. Since the tag only needs to listen and does not need to broadcast, the operation is power-efficient. The Minibeacons have a theoretical range of maximum 70 m. Often, this range is smaller due to natural obstacles and reflection. Therefore, the practical range is about 50m, covering about one hectare of land. The idea is to put up a grid of beacons with 100 m in between each beacon. An overview of such a grid is visible in Figure 3.4, for 24 hectares of land.

If a more substantial area has to be covered, the nodes can be placed further away from each other, with the risk of not always being able to track the bird. This placement results in a grainier resolution but covers a larger area.

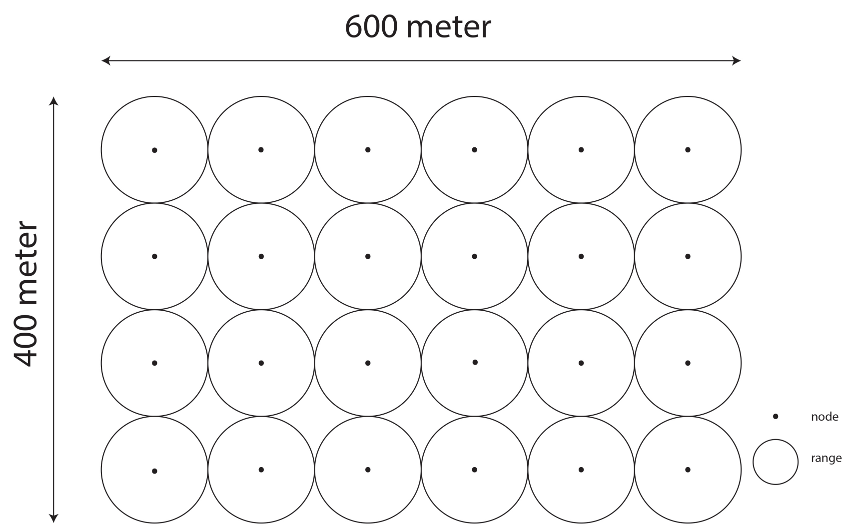

Figure 3.4: Grid of beacons to determine location

Chapter 4

Methods

The state-of-the-art in section 2 gives a clear overview of all available techniques. Next, we look at which of these are suitable for parakeet activity recognition and describe our used methods. We start with how we obtained the training data, next selected the features and show the developed algorithm. Finally, we show our how we tested our tracking part.

4.1 Data Collection

In total, we did three measurements on three different bird species. We tested on an owl, a falcon and a parakeet. During each measurement, data collection was done with the Axy-Trek logger, as explained in section 3.6. For our measurements, only the accelerometer was activated since the other sensors were not available on the development tag, the AKMW-iB001M. The accelerometer was sampled at 100 Hz, with a G fullscale of 8g and an 8-bit resolution, resulting in a timestamp and accelerometer values for the x-,y- and z-axis.

4.1.1 Owl

The first measurement took place in ”Wonderwereld”, a small zoo in Ter Apel (Netherlands), with the permission from the park’s owner. The logger was placed on the back of the owl (see Figure 4.1A). One manually controlled camera was used to follow the bird. The measurement with the owl was done in the open air, with the help of one of the zookeepers. In this way, the owl would perform actions on command, resulting in an equal distribution of activities. Measurements were done for 30 minutes after which the owl refused to follow commands. Therefore, the experiment was seized. Within this time, no sufficient data to train a machine-learning algorithm was gathered. We will give a small overview of the measured activities in Table 4.1.

Activity	Owl	Falcon
Standing	664	91
Flying	50	15
Picking	12	72
Soaring	1	0
Eating	53	0
Unknown	107	345

Table 4.1: Data entries per activity of the owl and falcon

4.1.2 Falcon

Since our target animal was not available in this first measurement, we also measured on a falcon. ”Falcons have a similar wing frequency as parakeets”, according to the bird expert B. Toxopeus. Therefore, we expect that the activities of a falcon produce the same data as those of a parakeet. Also, we used the data from the falcon to compare it to the owl so that we could use the data gathered from the owl within our algorithm training.

This measurement also took place in ”Wonderwereld”, directly after the measurement with the owl. The logger was placed on the back of the falcon (see figure 4.1C). Also, one manually controlled camera was used to follow the falcon around. A dead-spot was present in the corner above the camera. The falcon was placed in a small cage of $\sim 20m^2$, with a height of $3m$, limiting the time of flights. Only 10 minutes of data were gathered since the available zookeeper had to go, and no experiments were allowed without their supervision. The gathered data is in Table 4.1.

4.1.3 Parakeet

The owl data and the falcon data were nothing alike, and thus, both datasets were excluded in the research. Therefore, a third measurement needed to take place. This time a rose-ringed parakeet was available (see figure 4.1B). The measurements took place at the ”World of Birds foundation”, a bird welfare foundation in Erica (Netherlands), with permission from the foundation’s owner. The bird was able to move around freely within a cage of $\sim 70m^2$, with a height of $3m$. Within the cage, multiple branches were placed to land onto, simulating a natural habitat for the bird. One measurement was done for 3 hours straight, gathering enough data to train a machine-learning algorithm. Two cameras where used, one manually controlled following the bird and the other in the corner for a wide-angle shot.

Figure 4.1: F.l.t.r. The tagged owl, the tagged parakeet, the tagged falcon

In total, around 941500 raw data points were collected. Statistics on these data entries can be found in figure 4.2. This shows all gathered activities in a 3D-scatter graph. Clear distinctions between standing, flying and shaking are visible, while the rest of the activities are tightly grouped. A logarithmic scale was used to show this grouping better. The activities that were observed during the day are listed in Table 4.2. These are labelled activities, which took place over 2 second windows.

4.2 Data Labelling

In order to use supervised learning methods, each data point must contain an additional label field indicating the class to which it belongs according to the ground-truth. Therefore, the ground-truth is deduced by video footage of the parakeet, which is synchronised with the sensor data. The labelling of the data was done through a Matlab GUI developed by Jacob Kamminga, allowing the annotation of the data according to video footage [52]. This labelling was done manually, and an example of the GUI can be seen in figure 4.3. While this GUI was initially used for labelling data sets of goats [69], it worked well for labelling bird activities with minimum modifications to the code.

We annotated the data according to the behaviours listed in Table 4.2. At all times, we labelled the activity and did not include transitions within our labels. Therefore, some labelled data includes a transition phase to another activity. If this transi-

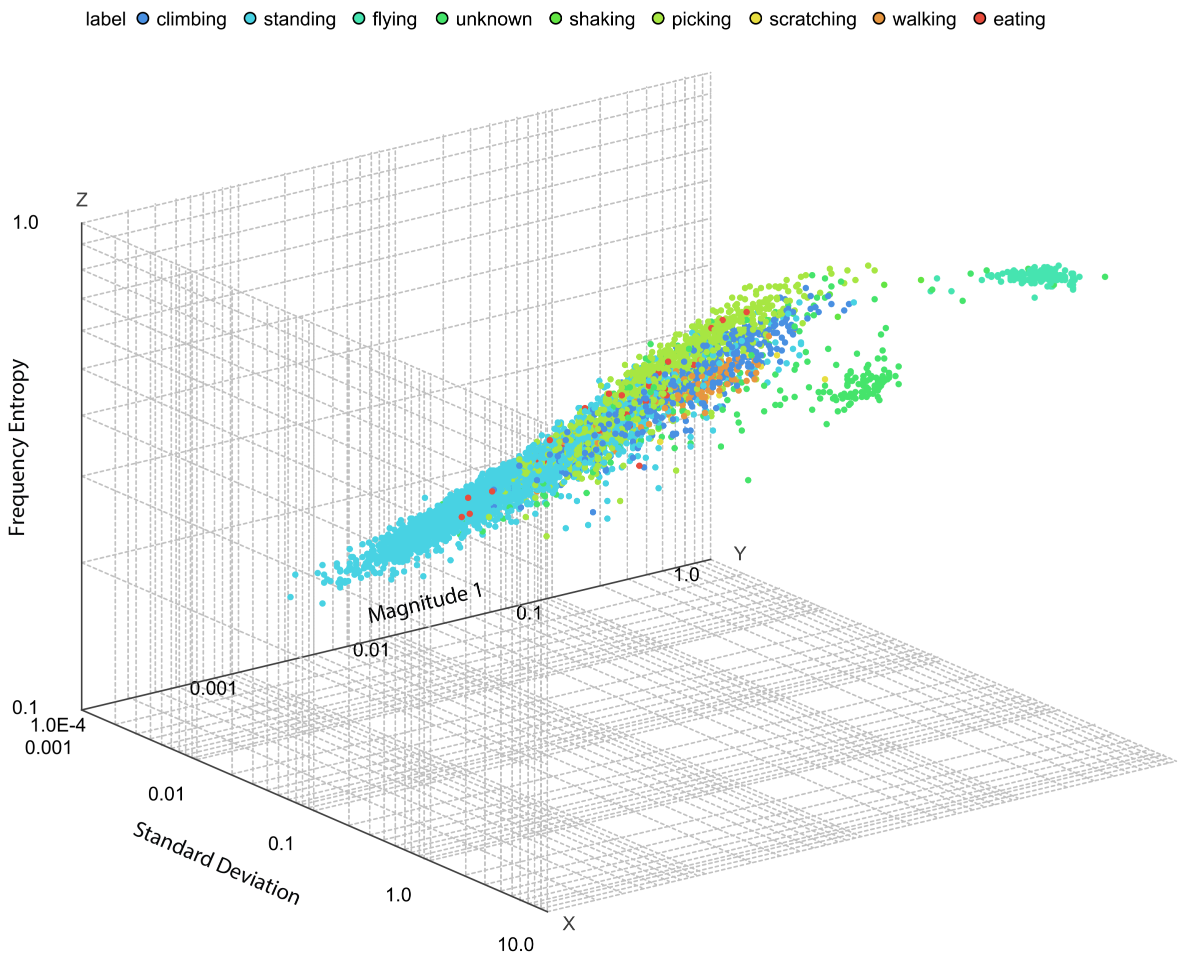

Figure 4.2: Statistics of the parakeet data set on a logarithmic scale

Figure 4.3: An example of the matlab GUI

Activity	Description
Standing	The animal is standing still, occasionally adapting its posture.
Flying	The animal is flying and is not in contact with the ground.
Picking	The animal picks with its beck. This is done either to see if it can remove the tag or to put its feathers straight.
Shaking	The animal is shaking its entire body in a very rapid motion.
Jumping	The animal jumps up or down from one place to another.
Climbing	The animal moves across or up/down a branch or fence.
Walking	The animal walks across the ground without using its wings. The pace is almost always the same.
Scratching	The animal scratches its head/body with its claw.
Eating	The animal eats some seads.
Unknown	Any other activity which could not be placed properly underneath the mentioned activities above.

Table 4.2: Observed activities during the day

tion was unclear, it would be labelled *unknown*.

4.3 Data Processing & Feature Selection

The dataset of the parakeet was segmented according to the labelling file. The segments were split into 70% training data and 30% test data. Data were segmented with a two-second window size and a 100 Hz sample rate. We overlap consecutive windows to alleviate the effects of edge conditions, which occur when windows are segmented sequentially. Therefore, segments are generated with an overlap size of 50%.

Table 4.3 shows the number of data points for each class for both the training and testing data. Noticeable is the lack of entries for jumping, shaking, scratching and eating. These four activities did not take place for longer than 2 seconds or did not occur so often. Therefore, we will reduce the classification activities to six classes; *standing*, *flying*, *picking*, *climbing*, *walking* and *other* (which include *jumping*, *shaking*, *scratching*, *eating* and *unknown*).

Another noticeable observation is the difference in entries for standing versus the other activities. To calculate the balance of our dataset, we use Shannon entropy [79] to 'rate' our dataset, where 0 is an unbalanced data set and 1 a balanced data set. Equation 4.1 is used, where n is the number of instances, k the number of classes with size C_i. This results in a balance score of 0.529, meaning the set is

Activity	Training set	Testing set
Standing	4256	1767
Flying	96	50
Picking	760	325
Shaking	4	1
Jumping	0	0
Climbing	354	181
Walking	111	32
Scratching	9	1
Eating	28	2
Unknown	177	123

Table 4.3: Data entries per activity of the parakeet

slightly balanced.

$$Balance = \frac{H}{\log k} = \frac{-\sum_{i=1}^{k} \frac{C_i}{n} \log \frac{C_i}{n}}{\log k} \tag{4.1}$$

Finally, we calculate the time domain and frequency domain features for each window. Table 4.4 gives an overview of which features are calculated and adds a small description per feature. These features are used to train our algorithms. However, since we do not want to use all features on our embedded platform due to energy constraints, we do three tests. The first test includes all features, the second only frequency-domain features and the final test only time-domain features. We test this for NN, DT and SVM since they are the three most commonly used algorithms. Finally, we compare F1-scores and accuracy versus the required power.

We also apply forward selection (as described in section 2.1.2) to see if we can reduce our feature set. Forward selection selects the following features:

- Mean
- Standard Deviation
- 25 percentile
- Skewness
- Principal frequency
- Frequency Entropy
- Magnitude of the fourth FFT component

Feature	Description
Maximum	Maximum value
Minimum	Minimum value
Mean	Average value
Standard deviation	Amount of variation
Median	Middle value
25 percentile	Value below which 25% of the observations are found
75 percentile	Value below which 75% of the observations are found
Mean low pass filtered signal	Mean value of DC components
Mean rectified high pass filtered signal	Mean value of rectified AC components
Skewness of the signal	The degree of asymmetry of the signal distribution
Kurtosis	The degree of 'tailedness' of the signal distribution
Principal frequency	Frequency component with the greatest magnitude
Spectral energy	The sum of squared discrete FFT component magnitudes
Frequency entropy	Measure of the distribution of frequency components
Frequency magnitudes	Magnitude of the first six components of FFT analysis

Table 4.4: All calculated features for each window

These might be the best features, but still, a combination of time-domain and frequency-domain features are used. Therefore, we repeat the same process only with time-domain features (which are also less battery expensive operations). This time the following features are selected:

- Minimum
- Standard Deviation
- Median
- 25 Percentile
- 75 Percentile
- Skewness
- Kurtosis

4.4 Algorithm Training

After preparing the data, we trained the algorithm. To do this, we used Rapidminer (version 9.3.001), a software tool for data preparation, machine learning, deep learning, text mining, and predictive analytics. Rapidminer uses a drag-and-drop system to compare different algorithms with each other easily. In Figure 4.4 an example of such a pipeline is visible.

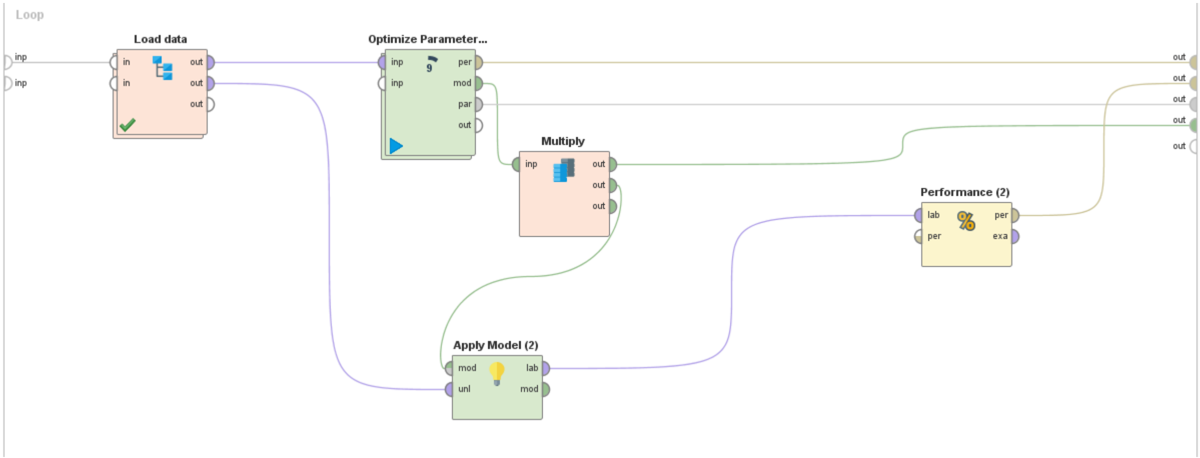

Figure 4.4: Example of a process in Rapidminer

We compare the algorithms mentioned in Section 2.1.3. The basic parameters are used in Rapidminer, and each algorithm uses the same features as explained in Section 4.3. Therefore, results will not be optimal for each algorithm. The six algorithms will be tested on the same data set of the parakeet. The best performing one will be optimized and then implemented on the wildlife tag.

4.5 Tracking

To determine the range of the Minibeacons, we put three Minibeacons in an open square and measured the RSS. The measurements were done on the O& O-square on the University of Twente (see Figure 4.5). This is a square where many people and thus signals pass-by, simulating an urban environment. Three Minibeacons were placed at one end of the square and measurements were done at 1, 11, 21, 31, 41 and 51 m distance. Each measurement was done twice, resulting in six measurements per position.

We measure the RSS values over 9 seconds at a rate of 10 Hz. An example is given in Figure 4.6. The RSS values are given in dB, and an average is calculated. If the values go below -100 dB the device is not shown.

Figure 4.5: O& O-square on the University of Twente grounds

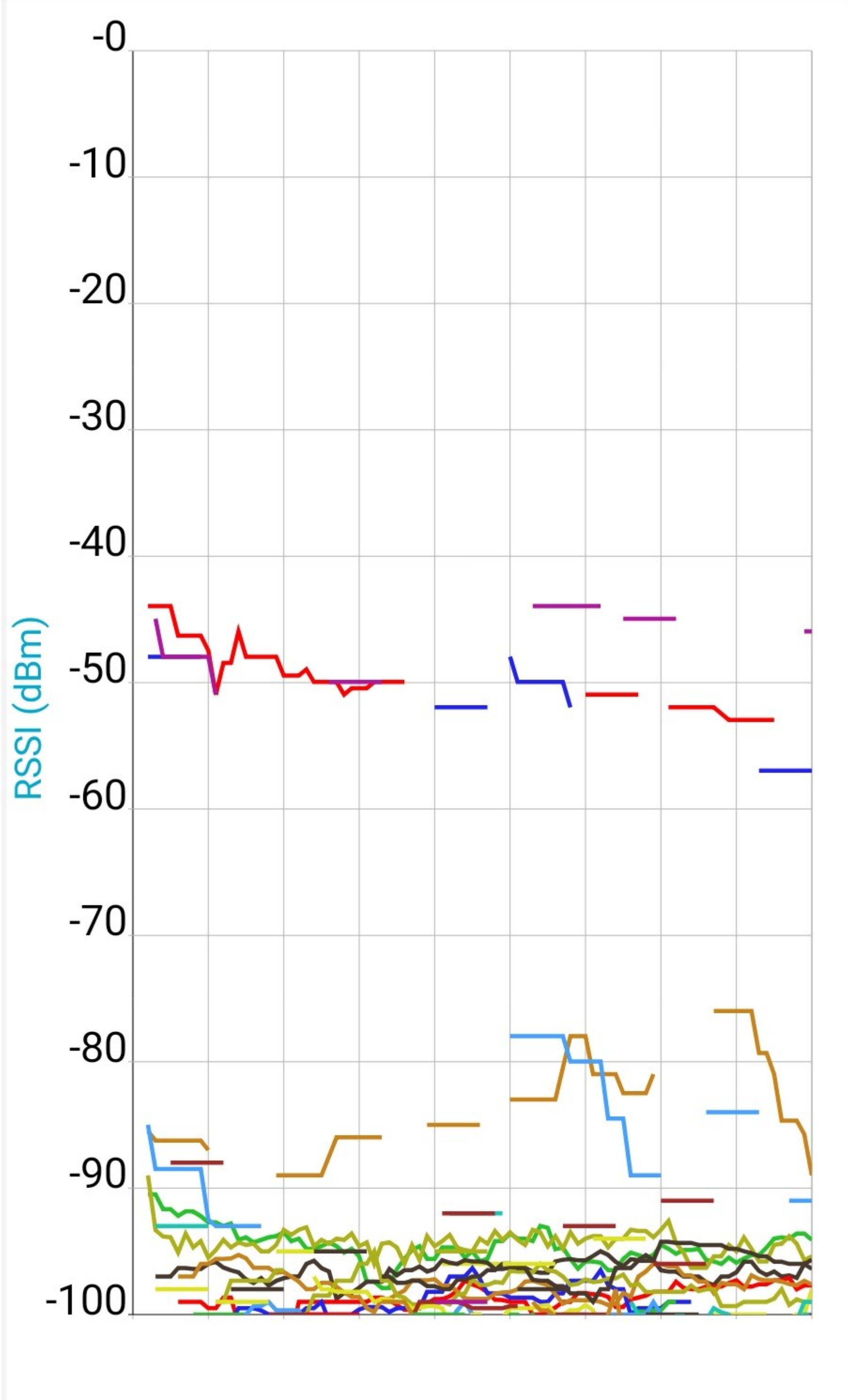

Figure 4.6: RSS measurement example

Chapter 5

Results

Within this section, we show the performance of the behaviour classification and our final implementation.

5.1 Behaviour Classification

We compare the use of different features sets as described in Section 4.3, all with the parakeet dataset. The results are visible in Figure 5.1. As accuracy only gives a prediction on the correctly predicted observations, we also want to include our False Positive (FP) and False Negative (FN). Therefore, we include an average F1-score. Equation 5.1 is used to calculate the F1-score.

$$\begin{aligned} Precision &= \frac{TP}{TP+FP} \\ Recall &= \frac{TP}{TP+FN} \\ F1 &= (\frac{Precision^{-1}+Recall^{-1}}{2})^{-1} \end{aligned} \tag{5.1}$$

We see a clear difference in the F1 scores when only time-domain features are used; however, the accuracy stays around the same. Another thing to note is that the NN performs better overall except when the time-domain features are used. While it is clear that the best performance is given by using all the features, we choose to use only time-domain features since they are computationally inexpensive. In the following experiments, we use the forward selection feature set described in Section 4.3.

Figure 5.2 shows the average accuracy and F1-score of our trained algorithms. We notice for *other* activities almost no correct predictions are made in this class. This has multiple reasons. First of all, not much data is available for this class (see table 4.3). Next, all data points are spread out and thus non-consistent when training the algorithm. Finally, many of these *other* activities resemble one of the other five

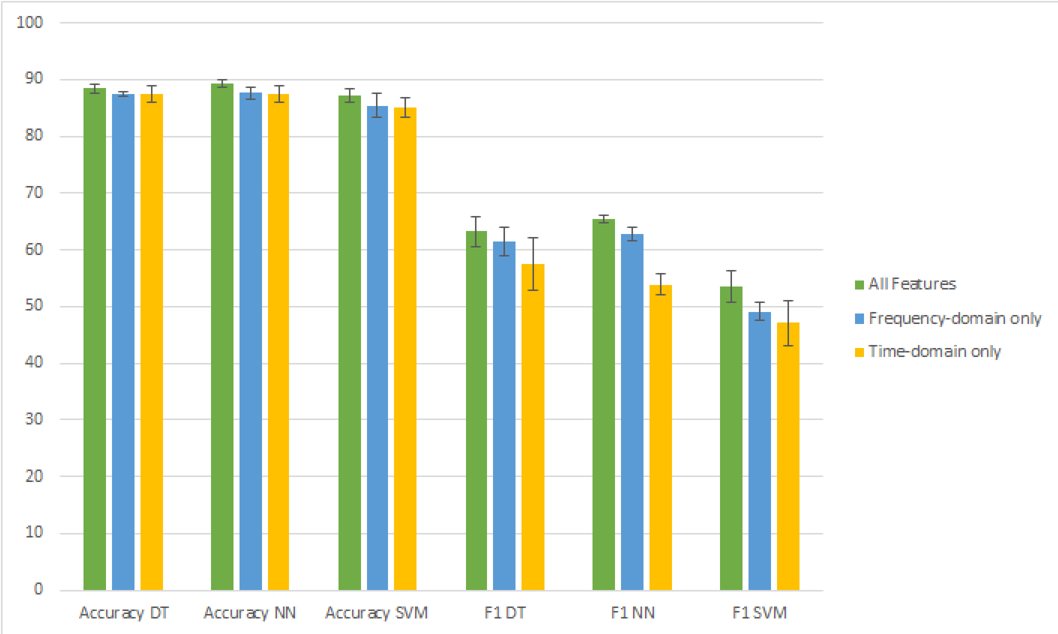

Figure 5.1: Performance of DT, NN and SVM with different feature sets

activities. For instance, the activity shaking looks like flying and eating like picking. Therefore, we also included the F1-score without the *other* activities. For further graphs, all F1-scores are calculated without the *other* category.

The top three performers are NB, NN and DT. k-NN, LDA and SVM had difficulties in distinguishing walking from picking and climbing.

5.2 Tracking

As described in Section 4.5, we measure the RSS to determine the range of the MiniBeacons. Figure 5.3 shows the results of this experiment. During the experiments it was sunny and about We did not receive any beacon at the 51-meter distance; therefore, it is not included in the graph. On 41 meter, we received only one beacon. The RSS of the other two beacons has been set to -110 dB to better depict the situation.

The range, therefore, is a maximum of 40 meters.

5.3 Implementation

For the final implementation in the AKMW-iB001M beacon, we use the decision tree, since this is easy to implement, performed well and does not cost much energy. Another option would have been the NB algorithm since it performed equally to the DT.

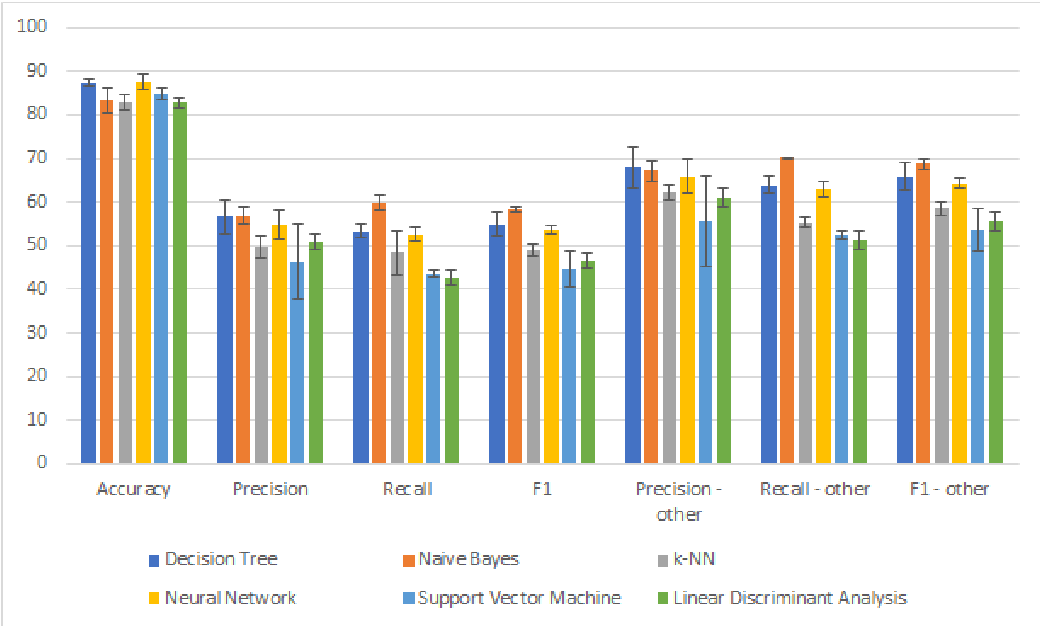

Figure 5.2: The performance of the different machine learning algorithms

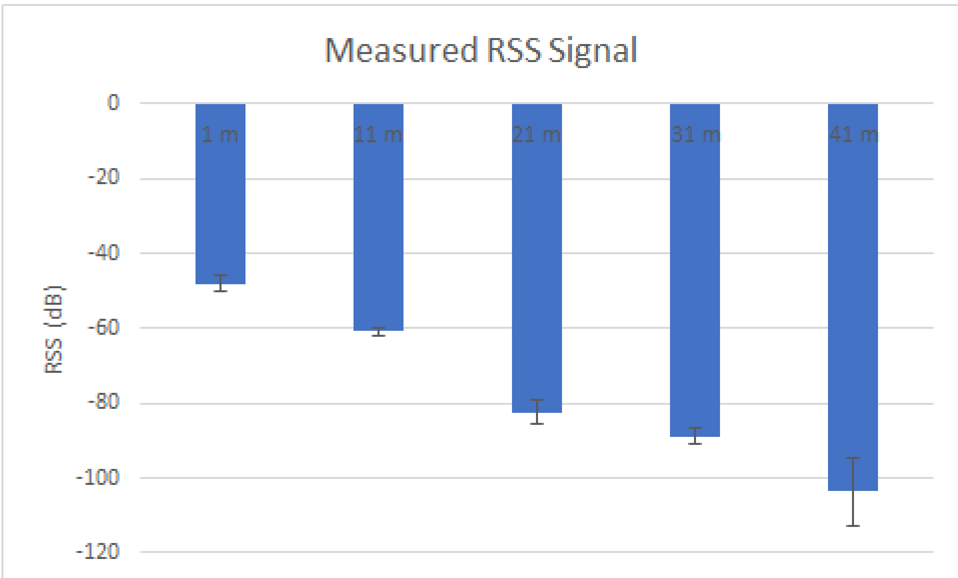

Figure 5.3: RSS measured on different locations

Parameter	Description	Value
Splitting criterion	The criterion which decides which attributes will be selected for splitting.	Information gain
Maximal depth	The depth of a tree varies depending upon the size and characteristics of the ExampleSet. This parameter is used to restrict the depth of the decision tree.	9
Apply pruning	Branches are replaced by leaves according to the confidence parameter after generation of the model.	True
Confidence	This parameter specifies the confidence level used for the pessimistic error calculation of pruning.	0.4
Apply prepruning	This parameter specifies if more stopping criteria than the maximal depth should be used during generation of the decision tree model. If true, the parameters minimal gain, minimal leaf size, minimal size for split and number of prepruning alternatives are used as stopping criteria.	True
Minimal gain	The gain of a node is calculated before splitting it. The node is split if its gain is greater than the minimal gain. A higher value of minimal gain results in fewer splits and thus a smaller tree.	0.1
Minimal leaf size	The size of a leaf is the number of Examples in its subset. The tree is generated in such a way that every leaf has at least the minimal leaf size number of Examples.	2
Minimal size for split	The size of a node is the number of Examples in its subset. Only those nodes are split whose size is greater than or equal to the minimal size for split parameter.	4
Number of prepruning alternatives	When split is prevented by prepruning at a certain node this parameter will adjust the number of alternative nodes tested for splitting.	10

Table 5.1: Decision Tree parameters

However, the DT was implemented via nested conditional statements for decisions. Again 2 second windows were used since historically this proved most effective. No other values were tested. A visual implementation of the DT can be found in Appendix A.2. We tuned the parameters for the best settings with a grid search [80]. We used the accuracy of the algorithm versus tree size as our performance metric when tuning the parameters. A short description of each parameter and the final value can be found in Table 5.1.

As mentioned in Section 4.1, we also recorded data from a falcon and an owl. We added this to the training data to see if our results increased. The result can be found in figure 5.4.

Noticeable is the drop in precision and recall when the owl data is included. The falcon data increases our performance slightly and can be beneficial for our algorithm. However, all results with falcon data are within the error margin and thus not significant. We also look at similar activities and how well our classifier could recognize the activities. For the activities of the owl, we could predict the activities 'flying' and 'standing' with an average precision and recall of 97% and an overall accuracy of 80%. Other activities from the owl, like 'soaring' and 'eating', were only predicted with an average precision and recall of 4%. These activities are performed differently by owl and parakeet; therefore, the low precision and recall make sense. Activities of the falcon had a high precision from 98%. However, recall dropped to 75% and only a total accuracy of 60% was reached. We suspect this low accuracy comes from the use of a small data set.

This algorithm is implemented on the AKMW-iB001M beacon. Every 5 seconds, we classify two seconds of data. The classification is stored together with a sequence number.

For tracking, we implemented the tower identification method. This method was

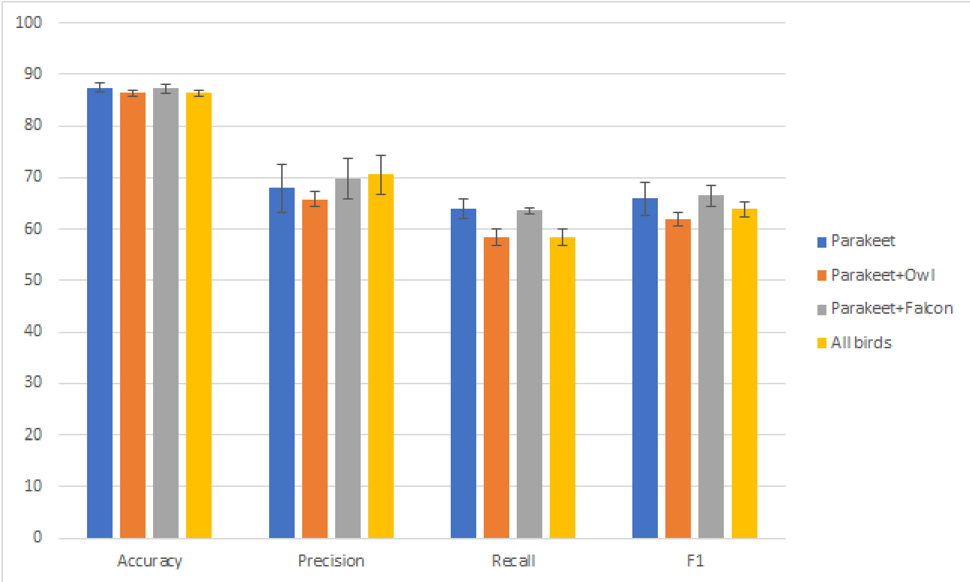

Figure 5.4: Performance of the decision tree with data from other birds included

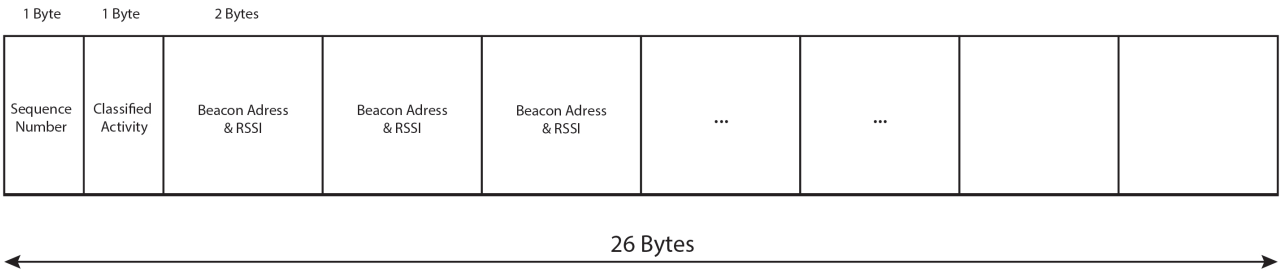

Figure 5.5: The 26 bytes which are stored

quick to implement and does not have complex computations. Every 5 seconds a scan is done for all different BLE devices in the neighbourhood. If the name of the tag starts with 'Minibeacon', the RSS value, the last byte of the address and a sequence number are stored. By linking the sequence numbers from the DT classifier and the tracker, we can determine where each activity took place. An example of a stored operation can be seen in Figure 5.5.

A high-level overview of the code can be found in Figure 5.6.

The current code takes up 90 kB flash memory and 14 kB Random Access Memory (RAM). Leaving 160 kB flash memory open for storage. Around 6000 store operations can be done before the memory is full. If every 5 seconds a scan is done, about 8 hours of measurements can be done before the memory is full. We expect this is enough to measure the daily activities of a bird. At the end of the day, the data will be offloaded, and the memory is cleared.

We also can calculate the time complexity of our DT. Let N = number of training

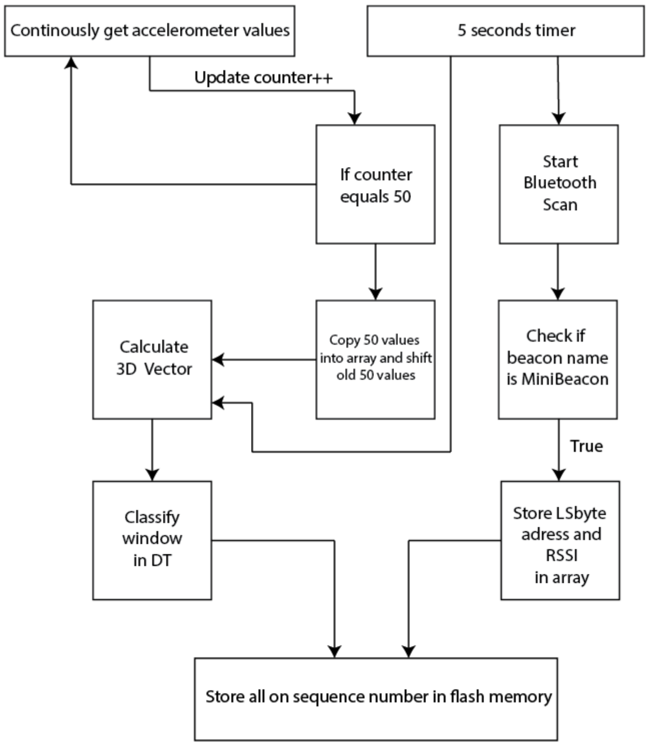

Figure 5.6: High-level overview of the code

examples, k = number of features, and d = depth of the DT. The time complexity of our DT is in $O(Nkd)$. Meaning it is between being in $O(N * 7 * logN)$ and $O(N^2 * 7)$.

Chapter 6

Conclusions and discussion

This chapter consists of conclusions about the results presented in Chapter 5 and gives some recommendations for future research.

6.1 Conclusions

Within this thesis, we showed the development of an AAR system for parakeets including location tracking. We implemented an AAR system for parakeets on an embedded device with a decision tree classifier. We have shown that with simple statistical time-domain features, it can compete with more sophisticated algorithms such as NN and SVM in terms of performance. While frequency-domain features performed better on F1-scores, each algorithm showed no significant differences in accuracy. To answer our main research question *"How can a bird activity recognition system be implemented on a small, light-weight and low-power embedded device?"*, we first answer each subquestion.

What are the trade-offs between accuracy and functionality against weight and energy? Sophisticated localisation techniques deliver better results but do require too much energy to be applicable. We used a low energy Bluetooth protocol to determine the location on a smaller scale. This protocol was well suited for parakeets since they are non-migratory birds. Again, this works less than solutions with GSM, but the energy constraint weighs more substantial than the accuracy. Another example of the energy constraints is that of the activity classifier. NN reached the highest accuracy but was not implemented since DT is more energy-efficient than NN. The main reason to design the tag power-efficient is the limiting hardware possibilities. As discussed before, the weight restriction resulted in a tag without a large battery. To let the tag operate at least one month, every operation needed to be low-power. Also, not much memory could be included, again limiting the tag. We minimized the loss in accuracy, but we can conclude that the weight and energy, weigh more substantial on the design of the tag than the accuracy and functionality.

When looking at the necessary localization infrastructure, again the trade-off between energy and functionality comes up. We chose to include more localization points to decrease the needed energy. The beacons only had a reach of 40 meter, which is significantly smaller than the theoretical 70 meters. The schematic that has been introduced (see figure 3.4) works well for small areas and minimizes the needed infrastructure. If one needs to measure on a broader scale, we suggest leaving more space in between the beacons. This gives a grainy resolution but keeps the same amount of required infrastructure. Another option is to put the beacons on locations which are known to be visited by the birds.

Looking at online activity recognition, we get a high accuracy for our decision tree. We reach an average accuracy of 87,35% for our parakeet dataset. An F1-score of 54,9 is obtained, which can be increased by filtering out *other* activities. Online activity recognition is possible for birds, but there are a lot of similar activities (except for flying and standing). These activities sometimes overlap (e.g. climbing and picking) and are hard to distinguish. Similar behaviour of the algorithm can also be seen when testing on the owl and falcon dataset. Flying and standing are distinct activities, while the other activities often overlap (see Figure 4.2). Overall we can accurately determine which activity is performed, but there is room for improvement for the other activities.

In the end, we can conclude that a bird activity recognition system can be implemented on a small, light-weight and low-power embedded device. The main issue with this implementation is the weight restriction of 5%, limiting the tracking and classifying techniques. However, with the use of low-power methods like BLE and DT, no massive battery is needed, while maintaining excellent performance.

6.2 Discussion

First of all, no final tests have been performed on birds with the designed tag. While it has the same algorithm running as the previous, we can not be sure the performance will match this tag. The designed tag will be tested and evaluated in the future on wild parakeets in Málaga, Spain. We look forward to seeing the results.

Though the proposed tag meets all set requirements, there are several ways to improve the system. A common thing within machine learning is that there is never enough data. Therefore, we recommend gathering more data from parakeets (on top of ours) to improve the algorithm. If a large dataset is collected, it is possible to make a balanced dataset. This would remove any biases caused by imbalance. A larger dataset would also be beneficial for less frequently occurring activities. These are now hard to classify due to the low number of samples and are merged into *other* activities.

Next, the mentioned localization techniques like AoA and TDoA increase the accuracy of tracking. In our proposed system the RSS is stored, indicating the distance to the beacon. However, with AoA, the angle can be determined and give a precise location of the tag.

Finally, the ICARUS project (as mentioned in Chapter 2 is a promising project to use GPS while remaining energy efficient. Unfortunately, our tag was not suited for this project. We highly recommend seeing if a tag can be designed in combination with this project.

One thing we would like to do differently within our research next time is the different use of tags. While the second tag (Axy-Trek) saved us much time, it had a different accelerometer than the AKMW-iB001M. This caused a difference in the accelerometer values used within the AAR algorithm. We minimized the effects by using the same frequency and scale, but the difference can occur through distinct hardware. Therefore, in future research, we suggest gathering data with the same accelerometer as will be used in the final product.

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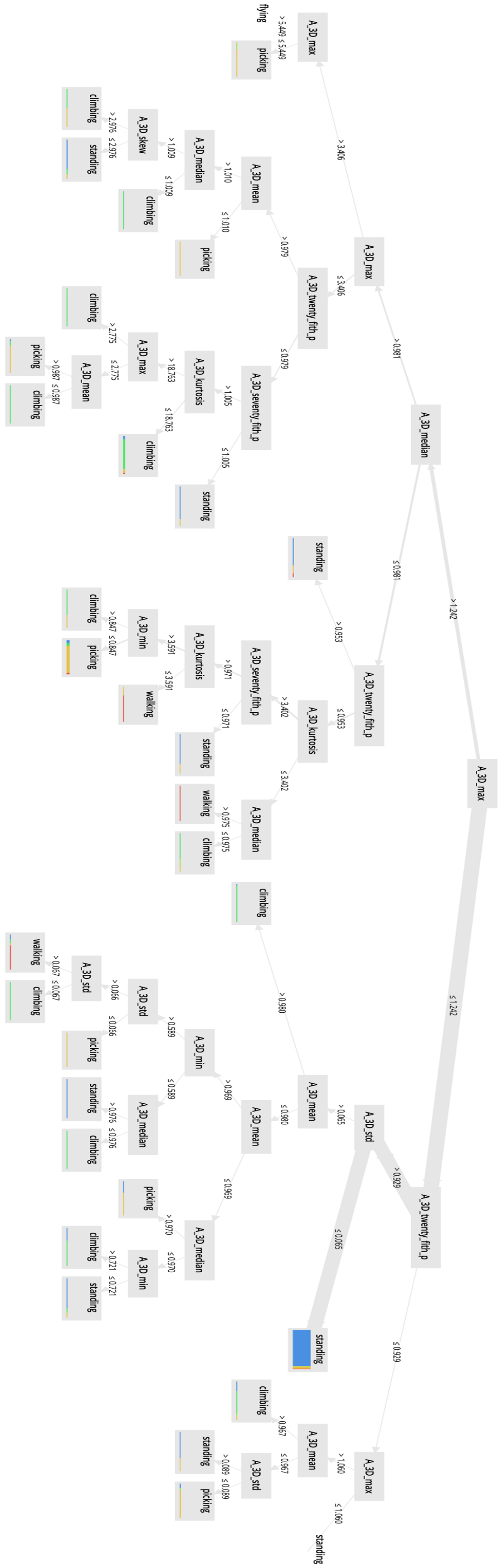
Appendix A

Appendix

A.1 AnkhMaway Beacon AKMW-iB001M

A.2 Decision Tree

Feature	iBeacon & Eddystone / Other Protocol User Defined
Chipset	nRF51822 256 KB 16kB
Bluetooth	BLE 4.0
Bluetooth Range	50 meters in open air
Operating Voltage	1.8v - 3.6v
Working current	3.6μA standby average, 21μA normal average
Side Pins for debugging	VCC, GND, SWDCLK, SWDIO
Working time	4.63 months based on broadcasting rate 1 second
Certifications	FCC/CE/MFI/RoHS
Sensor	Acceleration sensor
Buzzer	Yes
Size	40.3mm x 23.9mm x 2.6mm
Weight	6g


A_30_max
> 5.449 ≤ 5.449
flying
picking
> 3.406
A_30_max
≤ 3.406
A_30_mean
> 1.010 ≤ 1.010
A_30_median
> 1.009 ≤ 1.009
A_30_skew
> 2.976 ≤ 2.976
climbing
standing
climbing
picking
> 0.979
A_30_twenty_fith_p
≤ 0.979
A_30_seventy_fith_p
> 1.005 ≤ 1.005
A_30_kurtosis
> 18.763 ≤ 18.763
A_30_max
> 2.775 ≤ 2.775
A_30_mean
> 0.987 ≤ 0.987
picking
climbing
climbing
climbing
standing
> 0.981
A_30_median
≤ 0.981
A_30_twenty_fith_p
> 0.953 ≤ 0.953
standing
A_30_kurtosis
> 3.402 ≤ 3.402
A_30_seventy_fith_p
> 0.971 ≤ 0.971
A_30_kurtosis
> 3.591 ≤ 3.591
A_30_min
> 0.847 ≤ 0.847
climbing
picking
walking
standing
A_30_median
> 0.975 ≤ 0.975
walking
climbing
> 1.242
A_30_max
≤ 1.242
A_30_twenty_fith_p
> 0.929 ≤ 0.929
A_30_std
> 0.065 ≤ 0.065
A_30_mean
> 0.980 ≤ 0.980
climbing
A_30_mean
> 0.969 ≤ 0.969
A_30_min
> 0.589 ≤ 0.589
A_30_std
> 0.066 ≤ 0.066
A_30_std
> 0.067 ≤ 0.067
walking
climbing
picking
A_30_median
> 0.976 ≤ 0.976
standing
climbing
A_30_median
> 0.970 ≤ 0.970
picking
A_30_min
> 0.721 ≤ 0.721
climbing
standing
standing
A_30_max
> 1.060 ≤ 1.060
A_30_mean
> 0.967 ≤ 0.967
climbing
A_30_std
> 0.089 ≤ 0.089
standing
picking
standing