Expert-driven development of conservation technologies

to close knowledge gaps in small animal research

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Preface

I would like to take this opportunity to thank all those who have accompanied me on this challenging and inspiring journey.

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Abstract

To decelerate the human-induced extinction of species, humanity needs to mitigate its impact and implement effective conservation measures. This requires detailed knowledge about the behaviour and ecology of species generated by suitable observation methods. Hence, both efficient data-collection methods, and analysis tools are indispensable. Especially small species (<100g) are a challenge for classical field methods but also commercially available technical solutions reach their limits with decreasing body size.

This work addresses the challenge of making technologies, successfully used in current research practice, available for small animals (<100g) at low cost, and open source. The potential for successful transfer of technological developments into conservation practice and ways to ensure their continued availability are explored. To achieve these goals, this thesis addresses four research dimensions:

1. Sensor development

Tracking the movements of animals has provided ground-breaking insights into their behaviour, ecology, and interaction with their environment. Tracking involves equipping animals with different kinds of transmitters (GPS, accelerometers). However, the transmitters used are generally too heavy for small species.

One goal of this work was to develop a low-cost automated radio-tracking system, the tRackIT-system, that allows live tracking of movements, behaviour, and physiological states of small animals equipped with Very High Frequency (VHF) transmitters (weight <0.5g).

Camera traps are becoming increasingly popular in ecological research. However, their use for small animal species is limited due to the lack of sensitivity of the sensors used to trigger a recording. With the development of a multi-sensor tool (the BatRack) which combines acoustic and visual sensors with the tRackIT-system, the behaviour of small nocturnal animals (bats) can be reliably recorded. The combination of sensors also allows individuals to be recognised in video and audio recordings.

Both sensors were used to investigate the movements and behaviours of bats and songbirds and optimized for stable and permanent deployment over four years in the research forest of the Phillips-University Marburg (Marburg Open Forest (MOF)).

2. Data Analysis

Automation of environmental observation involves an increasing amount of data to be analysed. Appropriate tools for processing them are as important as the sensors themselves. In this work, various functionalities and tools, ranging from providing an exchangeable data structure to trained machine learning models for classifying behaviours in radio-tracking data and bat calls in sound recordings, were developed and made available open-source. Case studies on behaviours of different bat and songbird species demonstrate that relevant insights for conservation and ecological research can be generated using these sensors and analysis tools.

3. Practice transfer

Academically driven developments often remain at the status of prototypes, whose applicability in nature conservation practice by users with different degrees of technical expertise is not guaranteed. For the successful transfer to conservation practice, certain requirements must be met. The hardware and software must function reliably even under adverse field conditions, and access barriers such as the requirement of technical knowledge for implementation or costs must be kept low. In addition, the application range should be as diverse as possible.

The applicability of the tRackIT-system for various conservation-related issues was verified by two field tests. Firstly, wader chicks were tracked to be able to determine time and cause of their death with high temporal resolution. Secondly, it was tested whether the system can substitute labour-intensive and error prone manual methods in the context of environmental assessments in advance of the construction of wind turbines.

Both tests were a success in terms of saving labour and improving the data basis for conservation research and practice.

4. Long-term availability of technologies

One reason for the poor uptake of academically developed promising technologies in conservation research and practice results from the fact that technical support for users often ceases after the corresponding projects have ended. One way to ensure continued support and improvement of the technologies is to establish a company that provides this support as a service and drives further development.

The foundation of tRackIT-Systems company is supported by the EXIST program of the Federal Ministry of Economics and Climate Protection. The long-term access to the existing and future developments will thus be secured.

From the definition of demands to a user-oriented and feedback-driven development of permanently available products, this work realises all criteria for successful conservation technologies.

Zusammenfassung

Eine Voraussetzung für die Durchführung wirksamer Schutzmaßnahmen, um den vom Menschen verursachten Verlust von Tierarten zu verlangsamen, ist ein detailliertes Wissen über Verhalten und Ökologie der Arten. Um dieses Wissen zu generieren, sind sowohl effiziente Datenerhebungsmethoden als auch Analysewerkzeuge unerlässlich. Insbesondere kleine Arten (<100g) stellen eine Herausforderung für klassische Feldmethoden dar. Aber auch kommerziell verfügbare technische Lösungen stoßen mit abnehmender Körpergröße an ihre Grenzen.

Diese Arbeit befasst sich mit der Herausforderung Technologien, die in der aktuellen Forschungspraxis erfolgreich eingesetzt werden, für Kleintiere (<100g) kostengünstig und quelloffen verfügbar zu machen. Das Potenzial für eine erfolgreiche Übertragung technologischer Entwicklungen in die Naturschutzpraxis wird untersucht und Wege zur Sicherstellung ihrer kontinuierlichen Verfügbarkeit sowie zur langfristigen technischen Unterstützung der Nutzer werden sondiert. Dies wird durch die Bearbeitung von vier Forschungsdimensionen erreicht:

1. Entwicklung von Sensoren

Verschiedene Methoden zur Verfolgung der Bewegungen von Tieren haben in letzter Zeit bahnbrechende Einblicke in ihr Verhalten, ihre Ökologie und ihre Interaktionen mit der Umwelt ermöglicht. Beim Tracking werden die Tiere mit Sendern (GPS, Beschleunigungsmesser) ausgestattet. Die verwendeten Sender sind in der Regel zu schwer, um sie an kleinen Tieren anzubringen.

Ein Ziel dieser Arbeit ist es, ein kostengünstiges automatisches radio-Telemetriesystem, das tRackIT-system, zu entwickeln, welches die Live-Verfolgung von Bewegungen, Verhalten und physiologischem Zustand von Kleintieren ermöglicht, die mit VHF-Sendern (Gewicht <0,5 g) ausgestattet sind.

Kamerafallen werden in der ökologischen Forschung immer beliebter. Ihr Einsatz bei kleinen Tierarten ist jedoch aufgrund der mangelnden Empfindlichkeit der zur Auslösung einer Aufzeichnung verwendeten Sensoren limitiert. Mit der Entwicklung eines Multisensor-Tools (das BatRack), das akustische und visuelle Sensoren mit dem tRackIT-system kombiniert, konnte das Verhalten kleiner nachtaktiver Tiere (Fledermäuse) zuverlässig erfasst werden. Die Kombination der Sensoren ermöglicht auch die Erkennung von Individuen in Video- und Audioaufnahmen.

Beide Sensoren wurden über vier Jahre im Forschungswald der Philipps-Universität Marburg (Marburg Open Forest (MOF)) zur Untersuchung der Bewegungen

und Verhaltensweisen von Fledermäusen und Singvögeln getestet und für einen stabilen und dauerhaften Einsatz optimiert.

2. Datenauswertung

Mit der Automatisierung des Umweltmonitorings steigt auch die Menge der zu analysierenden Daten. Geeignete Werkzeuge für deren Verarbeitung sind daher ebenso wichtig wie die Sensoren selbst.

In dieser Arbeit wurden verschiedene Funktionalitäten und Werkzeuge entwickelt, die von der Bereitstellung einer austauschbaren Datenstruktur bis hin zu maschinellen Lernverfahren zur Klassifizierung von Verhaltensweisen in Radio-Tracking-Daten und Fledermausrufen in Tonaufnahmen reichen, und Open-Source zur Verfügung gestellt. Anhand von Fallstudien zum Verhalten verschiedener Fledermaus- und Singvogelarten wurde gezeigt, dass mit den Sensoren und Analysewerkzeugen relevante Erkenntnisse für den Naturschutz und die ökologische Forschung gewonnen werden können.

3. Transfer in die Praxis

Akademisch getriebene Entwicklungen verbleiben oft auf dem Status von Prototypen, deren Implementierung in der Naturschutzpraxis durch Anwender mit unterschiedlichem technischen Know-how nicht gewährleistet ist. Für einen erfolgreichen Transfer in die Naturschutzpraxis müssen bestimmte Voraussetzungen erfüllt sein. Die Hard- und Software muss auch unter widrigen Feldbedingungen zuverlässig funktionieren und die Zugangsbarrieren, wie z.B. das erforderliche Fachwissen für die Umsetzung sowie die Kosten, müssen niedrig gehalten werden. Außerdem sollten die Einsatzmöglichkeiten möglichst vielfältig sein.

Die Anwendbarkeit des tRackIT-systems für verschiedene naturschutzfachliche Fragestellungen wurde in zwei Feldversuchen überprüft. Zum einen wurden Watvogelküken getrackt, um ihren Todeszeitpunkt und die Todesursache mit hoher zeitlicher Auflösung bestimmen zu können. Zum anderen wurde getestet, ob das System arbeitsintensive und fehleranfällige manuelle Methoden im Rahmen von Umweltverträglichkeitsprüfungen für den Bau von Windkraftanlagen ersetzen kann.

Beide Tests waren ein Erfolg in Bezug auf die Arbeitsersparnis und die Verbesserung der Datengrundlage für die Naturschutzforschung und Praxis.

4. Langfristige Verfügbarkeit von Technologien

Ein Grund für die geringe Verbreitung von akademisch entwickelten, vielversprechenden Technologien in der Naturschutzforschung und -Praxis liegt darin, dass die technische Unterstützung der Anwender nach dem Ende der entsprechenden Projekte oft eingestellt wird. Eine Möglichkeit, die kontinuierliche Betreuung und Verbesserung der Technologien sicherzustellen ist die Gründung eines Unternehmens, das diese Betreuung als Dienstleistung anbietet und die Weiterentwicklung vorantreibt.

Die Gründung der tRackIT-systems GmbH wird durch das EXIST-Programm des Bundesministeriums für Wirtschaft und Klimaschutz gefördert. Der langfristige Zugang zu bestehenden und zukünftigen Entwicklungen wird damit gesichert.

Von der Definierung des Bedarfs in Forschung und Praxis über eine Nutzerorientierte und Feedback gesteuerte Entwicklung von auf Dauer verfügbaren Produkten, realisiert diese Arbeit alle wesentlichen Bedingungen für erfolgreiche Naturschutztechnologien.

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List of acronyms

AAU	Audio Analysis Unit
AIC	Akaike Information Criterion
AP	Average Precision
ARTS	Automtatic Radiotracking System
AST	Audio Spectrogram Transformer
Atlas	Advanced Tracking and Localisation of Animals in real-life Systems
BAARA	Biological AutomAted RAdiotracking sytem
BW	Band Width
CAU	Camera Analysis Unit
CNN	Convolutional Neural Network
COTS	Commodity-Off-The-Shelf
CSS	Chirp Spread Spectrum
FFT	Fast Fourier Transformation
FOSS	Free and Open Source Software
HGAM	Hierarchical Generalised Additive Model
IUCN	International Union for Conservation of Nature
LOEWE	Landes-Offensive zur Entwicklung Wissenschaftlich-ökonomischer Exellenz
LoRa	Long Range Wireless Radio Frequency Technology
MFCC	Mel Frequency Cepstral Coefficients
ML	Machine Learning
MOF	Marburg open Forest
MQTT	Message Queuing Telemetry Transport
MSFB	Mel-Scaled Filterbanks
NLP	Natural Language Processing
OS	Operating System

PLP	Perceptual Linear Prediction
PSD	Power Spectral Density
ROC-AUC	Area Under the Receiver Operating Chracteristic Curve
SDR	Software Defined Radio
SNR	Signal to Noise Ratio
STFT	Short-time Fourier Transform
TE	Time Expanded
TDOA	Time Difference Of Arrival
ToA	Time on Air
UCI	University of California, Irvine
VAU	VHF Analysis Unit
VHF	Very High Frequency
ViT	Vision Transformers
WBN	the Wildlife Biologging Network

Introduction

1. Introduction

Human-induced climate change and habitat destruction have led to an unprecedented rate of species extinction worldwide (Cahill et al. 2013; Ceballos, Ehrlich, and Raven 2020). In addition to genetic diversity, ecological and behavioural diversity are also at the brink (Kühl et al. 2019; Wong and Candolin 2014). To meet global conservation goals, humanity needs to avoid and mitigate its negative impact on biodiversity, and significantly improve its abilities to monitor ecosystems, wildlife populations, and individuals (Lahoz-Monfort et al. 2019).

To assess the state of species and populations, study their behaviour and ecology, and identify potential threats, conservation practitioners and researchers conventionally rely on data collections carried out by human field workers (Burghardt et al. 2012; Giese 1996; Grover 1983; Altmann 1974; Tuia et al. 2022). The applied methods are often time-consuming, labour-intensive, expensive, potentially biased, reduced to a limited number of individuals that can be observed simultaneously, and may involve the disturbance of wildlife and risks for field workers (Tuia et al. 2022).

In addition to shortcomings in analogue field methods, there is a clear bias within conservation research towards larger and diurnal species in accessible areas (Yarwood, Weston, and Symonds 2019; Ford et al. 2017) due to their better observability and the associated higher probability of scientifically usable data (Santos et al. 2020). This bias results in knowledge gaps and unnoticed declines in populations of small species (Coomber et al. 2021; E. Y.-S. Chen 2021), as has been shown by the recently discovered dramatic decline in insect biomass (Wagner 2020). This is particularly problematic because within ecosystems, small animals perform important functions and they make up a large part of biodiversity (Cardoso et al. 2020).

For instance, with 1,400 species bats account for nearly one-fifth of total mammal diversity (Frick, Kingston, and Flanders 2020), and they contribute to important ecosystem services such as pollination, seed dispersal, and pest control (Kunz et al. 2011; Ghanem and Voigt 2012; Charbonnier et al. 2021). In contrast, more than one-third of all bat species are either listed as threatened by the International Union for Conservation of Nature (IUCN) or data is insufficient. More than half of the species show either a declining or unknown population trend. Nearly 1000 bat species or 80% of all known bat species need either continuing research or better protection (Frick, Kingston, and Flanders 2020).

Their small size, and secretive, and nocturnal habits in cluttered habitats (Wordley et al. 2018; Villarroya-Villalba et al. 2021) makes monitoring and research challenging.

Methods and technologies that can help fill knowledge gaps about the ecology of these elusive animals and identify threats are therefore urgently needed.

1.1 Conservation technology- opportunities and limitations

The information age brings about an ongoing improvement in the development of computer and information technologies. The miniaturization of devices, while increasing computer performance and reducing power consumption, has expanded our ability to collect, store and analyse data. Communication technologies enable the transfer of ever-bigger amounts of data in real-time (Maffey et al. 2015). In the field of ecology and nature conservation, technological advances in animal tracking, acoustic and image-based monitoring, remote sensing applications (Marvin et al. 2016) or machine learning algorithms have enhanced our understanding of ecosystems and their dynamics, which in turn has led to improvements in nature conservation and wildlife management (Berger-Tal and Lahoz-Monfort 2018; Allan et al. 2018; Pimm et al. 2015; Snaddon et al. 2013). Together the new technological opportunities are expanding the limits of traditional ecological research, giving rise to the presumption that ecology and conservation research are on the cusp of a revolution in data acquisition and analysis (Allan et al. 2018).

However, besides the technology enthusiasts celebrating the dawn of a new era in conservation research, there are a growing number of recent studies examining why conservation technology has not lived up to the expectation to assist on-the-ground conservation fast and at a global scale (Lahoz-Monfort et al. 2019; Speaker et al. 2022).

The key to game-changing innovations in conservation technology has been identified in close collaboration between end-users defining real-world requirements and obstacles, and technologists such as engineers and software developers who bring the abilities for development and adaptation of custom technologies (Berger-Tal and Lahoz-Monfort 2018; Hahn, Bombaci, and Wittemyer 2022) to tune their functionality to the actual requirements (Pearce 2012).

In contrast to this ideal development model, innovations in conservation technology are often driven by academic motivations, highlighting the potential of new methods, sometimes generating exciting results. However, they often remain on the status of demonstrators or prototypes, thus not fulfilling criteria such as low technical knowledge barriers, secure energy supply, stability under field conditions, and user support extending beyond the lifetime of projects, resulting in a limited transfer into research and conservation practice (but see the AudioMoth, Hill et al. 2019). Those results that are taken up by technology firms to turn them into products often lose the features most critical to the community's needs, also resulting in the exclusion of poorer parts of the world due to proprietary solutions at high costs (Hahn, Bombaci, and Wittemyer 2022; Berger-Tal and Lahoz-Monfort 2018; Lahoz-Monfort et al. 2019; Ravindran 2020).

Commercially available technical solutions also reach their limits as the body size of species decreases. For instance, due to fast improvements in tracking technology in the last years, the number of locations per animal increased from a few dozen points in space, generated by manual VHF telemetry, to millions of movement steps from GPS tags, and satellite-based telemetry enabling ecologist to unravel a vast field of open questions (Whyte, Ross, and Buckley 2014; Yockney et al. 2013; Freeman et al. 2010; Torres et al. 2011). However, GPS transmitters that provide high temporal resolution with a runtime of several days have not yet been developed for animals with a body mass <100g (McMahon et al. 2017).

Camera traps are applied to monitor a wide range of ecosystem variables such as abundance, diversity, and distribution of animals (O'Brien and Kinnaird 2011; Li, Bleisch, and Jiang 2018). A single trap, unlike most other sampling methods, can operate day and night over a long period without maintenance, collect a large amount of data and detect many of the animals present (Wearn and Glover-Kapfer 2019) but infrared sensors used to trigger camera traps have detection rates below 25% for birds of tit size and smaller (Randler and Kalb 2018).

The technological possibilities for solving the above problems exist. The challenge is to make them work for conservation research.

1.2 Research needs and contribution of this thesis

In summary, against a backdrop of massively accelerated species extinction and ecosystem degradation, the research community must do all it can to fill knowledge gaps to make informed decisions for biodiversity conservation. While recent technological developments have the potential to deepen our understanding of the ecology of many species, an unfavourable constellation of short-lived academic interest on the one hand and commercialization of selected technologies on the other, prevents the full realization of technological potential in ecological research and conservation. Especially the challenges researchers encounter when observing small and elusive species are not adequately addressed by currently available solutions.

A shift towards innovations driven by conservation experts accompanied by an open-source hardware, software, and data culture has the potential to provide ecological research and conservation practitioners, with accessible, affordable, and fit-for-purpose tools to address the complexity of nature and decelerate the decline in global biodiversity (Allan et al. 2018).

The Natur4.0 - Sensing Biodiversity Project, funded by the Hessen State Ministry for Higher Education, Research and the Arts, Germany, as part of the LOEWE priority program, brings together scientists from the fields of mathematics, computer science, geography, and ecology with conservation practitioners and experts from administration and the private sector. By taking advantage of this unique opportunity, this thesis aims to develop and assess low-cost and open-source technological solutions and data analysis tools with high usability, for the tracking and visual and acoustic observation of small animals including the recognition of individuals. The potential for a successful transfer into conservation practice is assessed and strategies for permanent availability and continuous technical support beyond the lifetime of academic projects will be outlined. While focussing on the applicability for small animals in general, bats serve as model organisms due to their importance for biodiversity and ecosystem functions and the challenges they pose for researchers.

1.2.1 Research dimensions

The above-mentioned research gaps and requirements for appropriate field methods result in four research dimensions that are addressed in this thesis.

Research dimension 1: Development and assessment of low-cost and open-source software and hardware designs that enable automatic individual monitoring and behavioural observations of small animals

Among the main drivers of new ecological knowledge in recent years are the development of tracking technologies such as GPS transmitters and visual and acoustic sensors that can automatically detect animals in their natural habitat without disturbance by field workers. However, technologies placed on animals to track their movements and behaviour are usually not allowed to weigh more than 5% of their body weight. Sensors such as camera traps, that are designed to locally detect species occurrence, are not sensitive enough to detect small species. Individual recognition, which is necessary for many research questions, fails even with solutions that are otherwise successful in detecting small animals (for example, ultrasonic detectors for bats).

It is, therefore, necessary to find sensory solutions for movement tracking and visual and acoustic monitoring of small animal species that also allow for individual recognition. Further properties that these developments should bring with them for stable use in the field are low-cost hardware, usability, durability, and power efficiency. Live transmission of data on the status of the sensors as well as transmission of the recorded data reduces the maintenance effort and provides a clear advantage in many nature conservation and research projects.

The tRackIT-system and its modular and mobile variant, the BatRack, provide solutions to the above-mentioned gaps in existing field technology. The tRackIT-system (Chapter 2.2, Gottwald et al. 2019; Chapter 2.3. Höchst and Gottwald et al. 2021) is an automatic radio-tracking system that was designed to permanently record signals emitted by VHF-transmitters as lightweight as 0.2g that are attached to animals to analyse their movements, behaviour and physical conditions in real-time. The BatRack (Chapter 2.4, Gottwald and Lampe et al. 2020) is a multi-sensor tool that combines radio-tracking, acoustic and visual monitoring into one soft- and hardware design. It enables the reliable camera recording of small (<10g) and fast-moving nocturnal animals (bats) as well as the recognition of tagged individuals in sound, video, and VHF recordings.

Four years of permanent deployment of the two systems under various conditions led to continuous improvements in the hardware and software designs, resulting in stable and reliable monitoring solutions for small animals.

Research dimension 2: Development of data-analysis tools and algorithms to analyse the collected data

Automation and the subsequent permanent deployment of sensors results in huge amounts of data. The handling and management of data can be an insurmountable challenge for many potential users and thus prevent the application of technological innovations (Hahn, Bombaci, and Wittemyer 2022). Furthermore, the collected data, even in a well-managed state, do not yet represent higher-level information that would be relevant to scientific questions. The acceptance and subsequent application of new sensors and monitoring devices thus partly depends on whether, in addition to data collection functionalities, user-oriented data processing tools and algorithms are developed.

To provide a solution for the processing of the collected data into analysable products, different functionalities and tools were developed as part of this thesis. First, algorithms were developed for processing the VHF signals recorded by the tRackIT-system and the BatRack into products such as positions and behaviour classifications using state-of-the-art machine learning (ML) methods (Chapter 2.2, Gottwald et al. 2019; chapter 3.2, Gottwald et al (in review)). These functionalities are provided as an R-package (https://github.com/Nature40/tRackIT) which also provides a standard data structure to facilitate the exchange of research projects and are made available as a live service, including their visualization enabling real-time monitoring of movement, physical state, and behaviour (Chapter 4.2).

To process and analyse the data collected by the camera and acoustic sensors of the BatRack an ML method for the classification of bat calls was developed and made available open source (Chapter 3.3, (Bellafkir et al. 2022)). This tool not only allows for the classification of bat species in sound data but also helps to reduce the simultaneously recorded video files to those most likely showing a bat of a certain species.

Research dimension 3: Potential for a successful transfer into conservation practice

Many exciting academic projects around the world have developed technical solutions to ecological problems, but these often remain on the status of prototypes and the transfer into conservation practice is rarely tested. The successful transfer of conservation technologies into practice involves defining the end users and their requirements, identifying and testing how and whether the offered product meets these requirements, and regularly updating the developments in feedback with the end users.

To test the potential for a successful transfer of the tRackIT-system into nature conservation practice it was deployed in two use cases involving different taxa and research aims. First, in collaboration with the Landesbund für Vogelschutz e.v., Bavaria, Germany (LBV) the tRackIT-system was deployed to track chicks of meadow breeding waders to investigate the timing and causes of chick mortality (Chapter 4.2). The second use case demonstrates the potential of the tRackIT-system to replace analogue and error-prone field methods in the assessment of risks of bat mortality and nature conservation act violations in advance of the construction of wind farms (Chapter 4.3). The feedback from both projects was used to further improve the product.

Research dimension 4: Strategies to ensure sustainable access to developments and continued technical support

Particularly in the field of conservation technology, innovative technological developments often emerge within the context of research projects with a short lifetime. It is often unclear how and for how long the technical support can be secured after the projects have expired. This circumstance often leads to the fact that helpful developments do not become established in practice.

Chapter 5 shows possibilities of how access to the technologies and support can be ensured after the end of the project within which the developments were made. The establishment of a company dedicated to the development of conservation technologies is presented as a possible solution.

Each of the research dimensions is treated as one chapter starting with an introduction that elaborates on the research needs and how this work contributes to them, followed by peer-reviewed publications as subchapters (Chapters 2 and 3). Research dimension 3 (Chapter 4) uses examples of real-world applications to show that the transfer of the presented expert-driven conservation technology into practice was successful, and research dimension 4 (Chapter 5) gives an outlook on how the necessary technical support for the implementation of comparable projects can be secured for the future.

Research dimension 1:

Development and assessment of low-cost and open-source software and hardware designs that enable automatic individual monitoring and behavioural observations of small animals

2. Introduction

The development of appropriate methods and technologies to collect and analyse data on the status and ecological properties of ecosystems, and the species that inhabit them (Marvin et al. 2016; Pimm et al. 2015), has become one of the most important tasks of environmental science (Allan et al. 2018).

Inexpensive but powerful single-board computers, such as the raspberry pi, are currently being regarded as one of the key technologies for the continuing revolutionisation of conservation technology (Jolles 2021). The ease of customisation and control, the quantity of compatible low-cost sensors, and the low energy consumption and durability of the devices enable scientists to build research tools that exactly meet their needs (Cressey 2017; Ravindran 2020; Kwok 2017).

In this chapter, the development and assessment of two single-board computer based sensor tools (the tRackIT-system and the BatRack) that enable researchers to study the movement and behaviour as well as the presence and abundance of bats, birds, and other small animals, is presented. Both tools are designed to operate autonomously in the field for long periods even under harsh environmental conditions. While the tRackIT-system is exclusively designed for the real-time monitoring of VHF-tagged individuals, the BatRack also collects video and sound data from unmarked individuals whereby the combination of acoustic and image recordings facilitates the data analysis.

2.1. The tRackIT-system

One of the most important recent technological innovations in terms of individual-level monitoring, providing ground-breaking insights into animal behaviour, cognitive sciences, evolution, and ecology, are high-throughput tracking systems delivering a high temporal resolution and spatial accuracy of individual movements (Nathan et al. 2022). GPS-based systems are readily available and able to record appropriately dissolved data, even transmitting positions in real-time. However their application for small animals <100g is still not realized due to the trade-off between battery size and weight, temporal resolution, and live time of tags, leaving radio-tracking with lightweight VHF-transmitters as the sole option for the tracking of small animals (Kays et al. 2015).

The most recent projects that realised the automation of lightweight-transmitter tracking are the automatic radiotracking system (ARTS) (Kays et al. 2011), the Biological AutomAted RAdiotracking sytem (BAARA) (Řeřucha et al. 2015), Advanced Tracking and Localisation of Animals in real-life Systems (ATLAS) (Weiser et al. 2016), the Motus Wildlife Tracking System (Motus) respectively sensorGnome (Taylor et al. 2017) and the

Wildlife Biologging Network (WBN) (Ripperger et al. 2020). Although breakthrough findings have been achieved in individual studies with the systems mentioned, their broad-scale application is limited by various properties. For ARTS and the BAARA, there is no current documentation that would allow for replication or even commercial acquisition of the systems, the Motus system is not designed for location tracking and does not allow for live data transmission, and ATLAS and WBN come with high technical knowledge barriers and costs.

One aim of this thesis is the development of a low-cost and open-source automatic radio-tracking system (the tRackIT-system) that allows for real-time data transmission and analysis to study the movements, physical condition, and behaviour of animals as lightweight as 2g. As a first step, we developed the hardware design and preliminary software for an open-source automatic radio-tracking system together with a basic localisation algorithm that enables the analysis of movement tracks of tagged individuals after the data has been collected in the field (Chapter 2.2, Gottwald et al. 2019).

While this first prototype was able to record the required data, it still suffered from various problems such as a high proportion of interference in relation to actual transmitter signals, high time drifts in the recorded signals, and an unstable operating system. Live data transmission was not realised at this stage of development. The further development of the prototype towards the tRackIT-system includes a substantially improved radio-tracking software, the tRackIT Operating system, that enables reliable VHF radio-tracking due to error handling functionalities and real-time data transfer using Internet of Things protocols (Chapter 2.3, Höchst and Gottwald et al. 2021). A stable, cost-effective, and easy-to-use automatic radio-tracking system is now openly available to the research community.

2.2 The BatRack

In addition to movement data, camera traps, and passive acoustic monitoring gained more and more popularity in the last decade (Frey et al. 2017; Wearn and Glover-Kapfer 2019). Despite their clear advantages, both methods have shortcomings concerning the observation of the behaviour of individuals of small species (Buxton et al. 2018).

Around the world, bats have been monitored with the passive ultrasonic recording of their echolocation calls (Milchram et al. 2020). They offer an easy way to monitor the presence/absence of bats but the possibility of recognising individuals is limited (Stowell et al. 2019). If one knows that a specific sound pattern is related to a particular behaviour, behavioural patterns can also be inferred from vocalisations. However, this knowledge is missing for many species (Teixeira, Maron, and Rensburg 2019).

Video recordings can help observe individual behaviour (Simpson et al. 2010; Schmidbauer and Denzinger 2019). However, commonly used cameras with infrared sensor triggers have a detection probability of 25% at maximum for species <20g even if the individual is within 1-metre distance of the sensor (Randler and Kalb 2018). Permanent video recording (Schmidbauer and Denzinger 2019) or taking pictures every few seconds (Corso, Woolley, and Lacher 2010) results in hundreds of hours of videos or millions of pictures that must be stored on the field device and examined by scientists (Jumeau, Petrod, and Handrich 2017) not to mention the massive increase in energy consumption.

The BatRack solves the problem of low detection rates and challenging individual recognition of small animals on camera traps and acoustic recordings (Chapter 2.3; Gottwald and Lampe et al. 2021) by combining a camera and an ultrasonic microphone with the tRackIT-system.

Introduction of an automatic and open-source radio-tracking system for small animals

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Introduction of an automatic and open-source radio-tracking system for small animals

Abstract

1. Movement ecology of small wild animals is often reliant on radio-tracking methods due to the size and weight restrictions of available transmitters. In manual radio telemetry, large errors in spatial position and infrequent relocations prevent the effective analysis of small-scale movement patterns and dynamic aspects of habitat selection. Automatic radio-tracking systems present a potential solution for overcoming these drawbacks. However, existing systems use customized electronics and commercial software or exclusively record presence/absence data instead of triangulating the position of tagged individuals.
2. We present a low-cost automatic radio-tracking system built from consumer electronic devices that can locate the position of radio transmitters under field conditions. We provide information on the hardware components, describe mobile and stationary set-up options, and offer open-source software solutions.
3. We describe the workflow from hardware setup and antenna calibration, to recording and processing the data and present a proof of concept for forest-dwelling bats using a mixed forest as the study area. With an average bearing error of 6.8° and a linear error of 21 m within a distance ranging from 65 m to 190 m, the accuracy of our system exceeds that of both traditional methods as well as manual telemetry.
4. This affordable and easy-to-use automatic radio-tracking system complements existing tools in movement ecology research by combining the advantages of lightweight and cost-efficient radio telemetry with an automatic tracking set-up.

2.2.1 Introduction

The analysis of animal movements based on tracking data enables ecologists to investigate questions related to habitat and resource utilization (Wyckoff et al. 2018), migration and dispersal (Cagnacci et al. 2010; Walton et al. 2018) or to build predictive models of animal behaviour (Browning et al. 2018). Recent improvements in tracking technology have increased the number of locations recorded per animal from a few dozen by manual radio telemetry to millions of movement steps from GPS tags and satellite telemetry, leading Kays, Crofoot, Jetz, & Wikelski (2015) to proclaim a new golden age of animal tracking (Kays et al. 2015). To complement this more finely resolved movement data, researchers have also developed a variety of sophisticated analytical techniques such as path segmentation analysis, step-selection functions and autocorrelated kernel methods (Fleming et al. 2015; Seidel et al. 2018).

Despite numerous advantages, both GPS tracking and satellite telemetry are still limited in their application to practical conservation and ecological research. The cost of tags notwithstanding, size and weight have limited their deployment in the past. New developments have successfully reduced the weight of such tags to ~1 g (e.g. PinPoint GPS tags, Lotek Wireless, Newmarket, CA). Nevertheless, battery lifetime and recording frequency are inversely related to weight, so the tags either record with low frequency or have short battery lifetimes (e.g. 5 nights for a 4.2 g GPS tag with a 30-s GPS-fixed schedule; (Roeleke et al. 2016)). Lightweight GPS tags also need to be retrieved to access the data (Hallworth and Marra 2015), which either directly or indirectly increases most studies' expenditures in the form of lost material or data (Smith et al. 2018; Tomkiewicz et al. 2010). These limitations aside, such tags are also too heavy for species weighing less than 20 g, as their weight should not exceed 5% of the individual's body mass to which it is attached (Brooks, Bonyongo, and Harris 2008). This leaves radio tags, with weights as low as 0.2 g, as the single option for 50% of European passerines (Bauer, Bezzel, and Fiedler 2012) and 80% of European bats (C. Dietz, Nill, and von Helversen 2016).

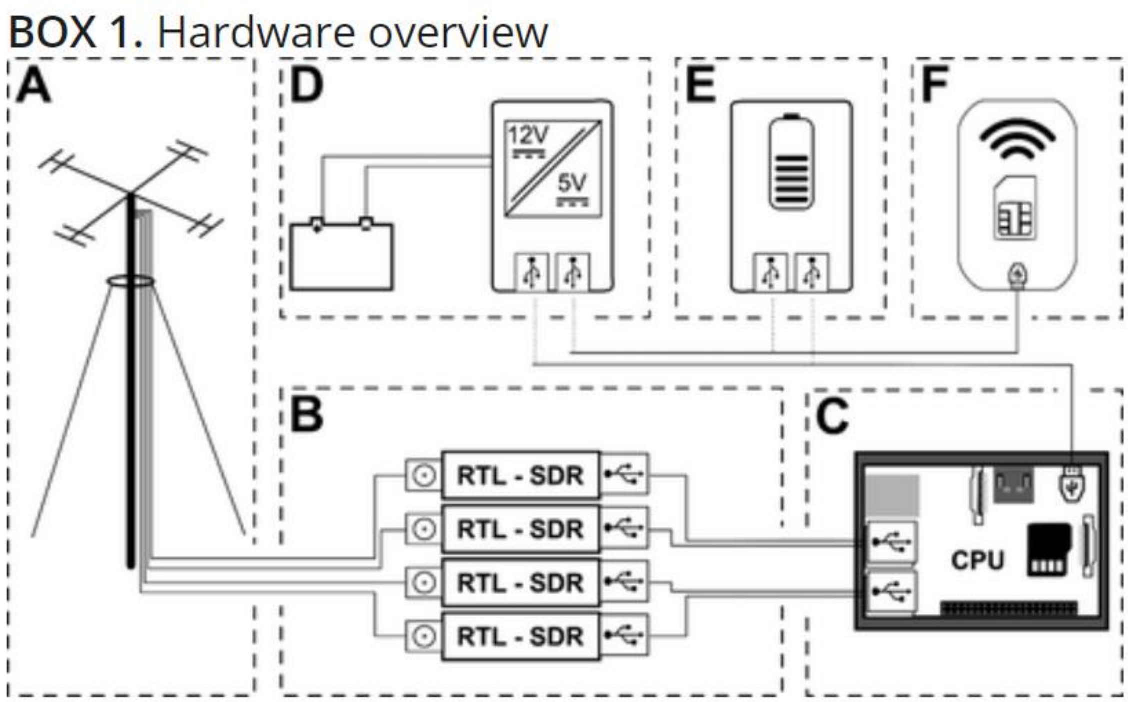
Manual radio telemetry has disadvantages including labour intensity, low temporal and spatial resolution (Montgomery et al. 2010; Thomas, Holland, and Minot 2011), infrequent and irregularly timed locations (Alexander and Maritz 2015), small sample sizes (usually one frequency at a time; (Kays et al. 2011)) and areal restrictions due to safety concerns for field workers (Smith et al. 2018). The quality of the resulting data also precludes any advanced analytical techniques created for fine-scale tracking data. Several working groups have designed automatic telemetry systems to overcome these drawbacks (Kays et al. 2011; Řeřucha et al. 2015; Weiser et al. 2016). Regardless of equipment, the key feature of modern automatic telemetry systems is a continuous signal record sent by radio tags using a stationary automatic receiver and a combination of either omnidirectional or directional Yagi-Uda antennae. The former can detect presence and absence, while the latter can detect the timing and direction of movement (Crysler, Ronconi, and Taylor 2016; Falconer et al. 2016). Existing systems use customized electronic devices with proprietary software (Kays et al. 2011; Weiser et al. 2016) or monitor presence and absence in large-scale movement studies, but cannot triangulate the position of a tagged individual (Taylor et al. 2017). Here, we describe an automatic radio-tracking system for locating individuals Zeidler, R. (2017) that has a high temporal and spatial resolution and works with inexpensive consumer electronics, flexible antenna designs and user-friendly, open-source software. In addition to a field test of system accuracy, we present a proof of concept based on forest-dwelling bats that illustrates the general use of the system under field conditions.

2.2.2 System Components and Methods

2.2.2.1 Core system

The low-cost, automatic radio-tracking system (Figure 2.1, A, B, C) consists of three basic elements: (a) a receiver chip, (b) antennae and (c) a single-board computer (e.g. Raspberry Pi). Common DVB-T television receivers with RTL2832U chips process the radio signal (e.g. Nooelec NESDR SMArt SDR, NooElec, NY USA). Inexpensive software-defined radios (RTL-SDRs, (Laufer 2015)) allow multiple radio signals to be simultaneously recorded. The RTL-SDRs connect the single-board computer with the Yagi-Uda antennae.

Figure 2.2: BOX1: Hardware overview



1. Station with four antennae positioned in the cardinal directions and tuned to the regional frequency for wildlife telemetry (around 150.100 MHz in Germany)

2. One RTL-SDR dongle per antenna (e.g. Nooelec NESDR SMart SDR, Nooelec, NY, USA) with a frequency range of 25–1,700 MHz and a maximal sample rate of 2 MHz (quadrature sampling)
3. Raspberry Pi 3B single-board computer (Farnell elements14, Leeds, UK) with the Raspbian operating system with a Docker-based architecture
4. High-capacity power supply with voltage regulation to work with the single-board computer, recommended for longer deployment times. Battery time can be further increased through solar panels and a solar charge regulator.
5. Power bank (20 Ah at 3.6 V), able to supply a station for ~8 hr, recommended for mobile setups
6. Mobile WiFi hotspot (Huawei E5330, Shenzhen, China), enables remote access within reach of the station's Raspberry Pi

To calculate the source direction of incoming signals, the antenna pole at a given station requires an array of at least three directional antennae (and an equal number of receivers) together with information about their orientation. The number of receivers that one computer can monitor depends on the number of available USB ports.

At least two antenna setups with known coordinates must be available and within the range of the radio source to triangulate the tag's position. Each station should be connected to the Internet to guarantee synchronized system times with e.g. a mobile Wi-Fi hotspot carrying a SIM card (Figure 2.3, F). The Network Time Protocol synchronizes the station times when they are first operational and approximately every 5 min thereafter.

The stations are operated using custom software. Operational hardware settings on the receiving units can be done by remote access in a user-friendly web-interface. This includes the setting of the monitored frequency band, activation of receivers as well as settings to reduce the recording of interference. Once the receivers are activated, they digitize incoming signals. An algorithm based on liquidSDR (Gaeddert 2019) automatically detects peaks in the radio signals along with timestamps, the frequency relative to a user-defined mid-frequency (Hz), signal bandwidth (Hz), duration of the signal (s) and signal strength (dB; For additional information see www.radio-tracking.eu).

2.2.2.2 Transmitter specifications

The system supports any type of radio tag common in wildlife radio telemetry. Individual tags are identified by their specific frequency. The number of tags that can be simultaneously monitored depends on the tag features and the possible width of the frequency band, as constrained by the CPU performance (e.g. 250 kHz for the Raspberry Pi 3 Model B, 1 MHz for the Model A+). With highly stable tag frequencies, tags can have frequencies as small as 1 kHz apart. Pulse timing is irrelevant for signal detection, which enables tags that transfer additional information (e.g. body temperature by varying time intervals between pulses) to be deployed. Tags are attached to the animal's skin, fur or feathers using skin glue that dissolves after a certain time. Alternatively, tags can be attached by e.g. harnesses and collars. Depending on the size of the tag, they can be operational between a few days and several months.

2.2.2.3 Principle of bearing calculation and triangulation

Signal amplification of a directional antenna depends on the angle of the incoming electromagnetic wave. The relation between the gain of a directional antenna and the angle of arrival can be approximated using a cosine function (Figure 2.2, Equation 1,(Rabinovich and Alexandrov n.d.)), where $g(\omega)$ describes the gain or loss relative to the angle ω in degrees compared to the gain of $\omega = 0°$.

$$g(\omega) = \frac{\cos\left(\frac{\pi}{90} \times \omega\right)}{2} + \frac{1}{2} \qquad (1)$$

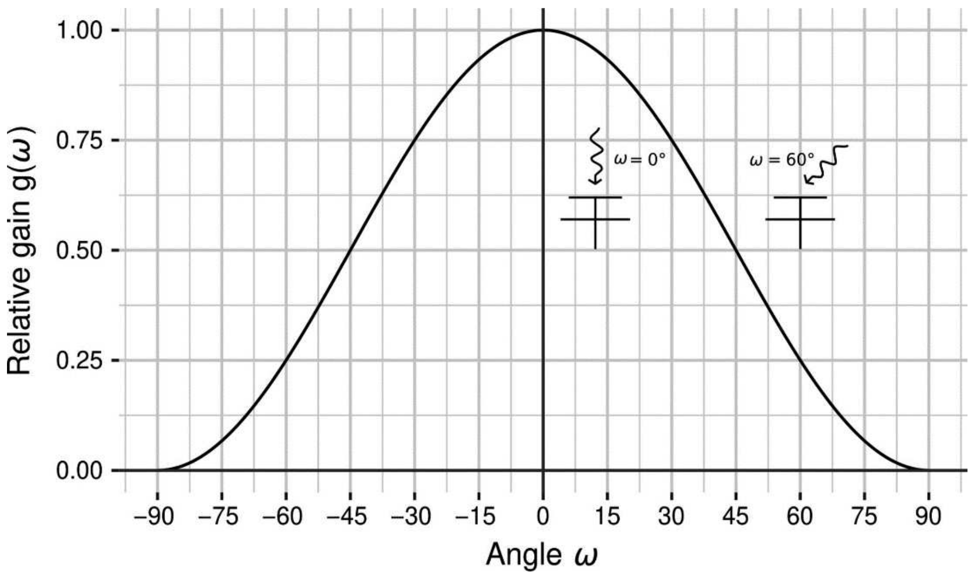


Figure 2.4: Radiation pattern of directional antennae

In comparing two antennae of the same design, the absolute gain in dB can be ignored because the values will be subtracted.

$$\Delta g\,(\omega, \alpha) = \frac{\cos\left(\frac{\pi}{90} \times \omega\right)}{2} - \frac{\cos\left(\frac{\pi}{90} \times (\omega - \alpha)\right)}{2} \tag{2}$$

$$\Delta g(\omega) = \cos\left(\frac{\pi}{90} \times \omega\right) \text{ with } \alpha = 90° \tag{3}$$

$$\omega = \frac{\pi}{90} \times \operatorname{arcos}\,(\Delta g) \text{ with } \alpha = 90° \tag{4}$$

Assuming that the propagation path of the incoming electromagnetic wave to the antenna is the same for both antennae (see also calibration), the direction of arrival (ω) of the transmitter signal is calculated by comparing the relative gains of two neighboring antennae (Equations 2, 3, 4) with α describing the angle between the antennae (Figure 2.3).

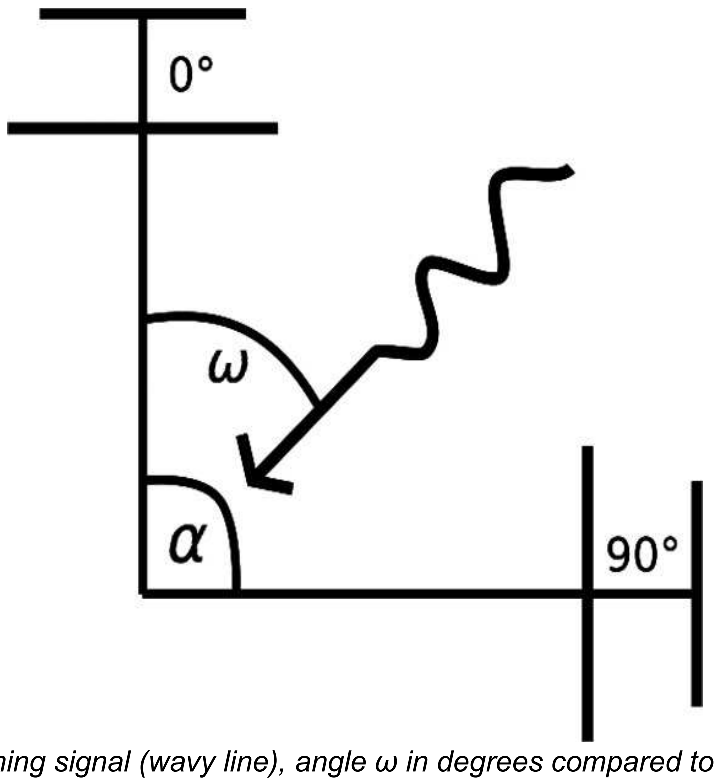


Figure 2.5: Incoming signal (wavy line), angle ω in degrees compared to ω = 0°, angle between antennae α

To calculate Δg in Equation 4, the difference in signal strength between the two antennae (*sl* and *sr*) is normalized with the maximum signal strength difference Δm (Equation 5).

$$\Delta g = \frac{(s_l - s_r)}{\Delta m} \tag{5}$$

This can be derived by either simulating the gain pattern of the antennae or a simple field experiment, in which the signal loss of the antenna pointing directly at the tag (0°) is compared to the signal loss of an antenna angled 90° relative to the tag. Therefore, the direction of arrival is a function of the normalized signal loss between the antennae and the angle between those antennae:

$$\omega(\Delta g, \alpha) = \left(1 - \cos\left(\frac{-\alpha \times \pi}{90}\right)\right) \times \left(\frac{1}{\alpha}\Delta g + \frac{1}{2}\right) \tag{6}$$

The tag's position is approximated by finding the point of intersection of two lines produced by bearing calculations at two separate stations. If more than two stations simultaneously receive the signal, the centroid of the resulting polygon is calculated.

2.2.2.4 Calibration

Recorded signals may differ in strength due to varying sensitivities of the components (e.g. antennae, cables, plugs, receivers). Since the bearing calculation relies on an equal net gain at each receiving arm, each arm must be calibrated. Calibration curves can be produced by mounting a transmitter at a fixed distance to the station and rotating the station around its vertical axis (Figure 2.4). Calculating the difference between each antenna's local maximum and the strongest local maximum signal returns a correction value for each receiving arm. Adding the correction value to the recorded signal strength adjusts every antenna to the same maximum signal strength.

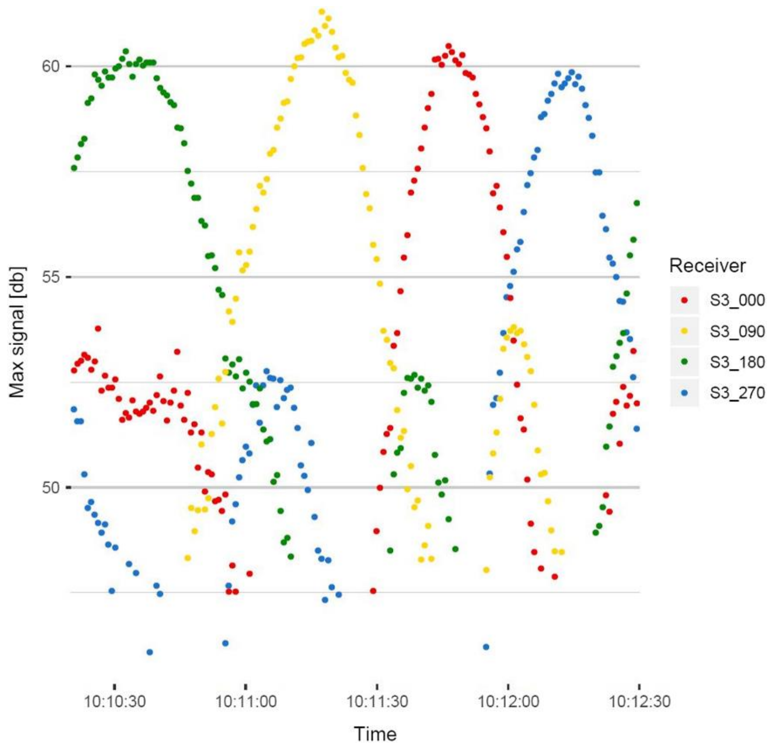


Figure 2.6: Calibration curves of four HB9CV antennae arranged in an array with 90° difference between neighbouring antennae (Station 3–S3). A radio tag was placed c. 115 m away and the array was slowly turned on its vertical axis

2.2.2.5 Data processing

Different processing workflows were tested to identify relevant settings and boundary conditions for obtaining optimal tracking results.

The bearing calculation requires that each receiving arm reliably record the signal. An individual antenna may drop a signal when the angle of the incoming electromagnetic wave strongly deviates from the angle of possible maximum gain (ω = 0°). Furthermore, very small or large intersection angles between bearings from two stations may produce erroneous or no triangulations, if bearings run parallel.

We tested the effect of available antennae on the accuracy of bearing calculations. The error of each bearing based on two, three or four receiving antennae was assessed by the difference in the calculated bearing and the angle between a station and the respective test position.

To assess the influence of intersection angles between bearings, we triangulated points and iteratively increased and decreased the allowed minimum and maximum intersection angle by 10°, respectively. For each set of triangulation points, we calculated the position error, which is the mean distance between the expected and measured positions.

Data were processed using R version 3.6.0 (R Core Team 2021). The functions are publicly available as an R Shiny analysis tool (https://github.com/radiotrackingeu/logger_app) or an r package (https://github.com/radiotrackingeu/radiotrackingeu).

2.2.2.6 Accuracy study on an empty field

In January 2019, we installed and tested this system on a bare field free of vegetation to assess the its potential accuracy and evaluate the data processing algorithm. The test setup comprised three stations, each equipped with four directional antennae (HB9CV, Telemetrie-Service Dessau) connected to RTL-SDR receivers (Nooelec NESDR SMArt SDR, NooElec). The system was mounted on 2.5 m tripods that were installed in an isosceles triangle formation with 200 m side length. The stations were calibrated against a transmitter at a fixed distance of 115 m. After calibration, a sighting compassed was used to position each station's antennae in the cardinal directions. A regular, 50 m-wide test grid was constructed between the stations and a 400 µW VHF radio-tag with a frequency of 150.203 kHz and a pulse interval of 0.7 s mounted on a 2 m pole was placed at each intersection of the test grid (Figure 2.5). The intersections and the stations were localized with a differential GPS. The distance of the radio-tracking stations to the test positions ranged from 65 m to 190 m.

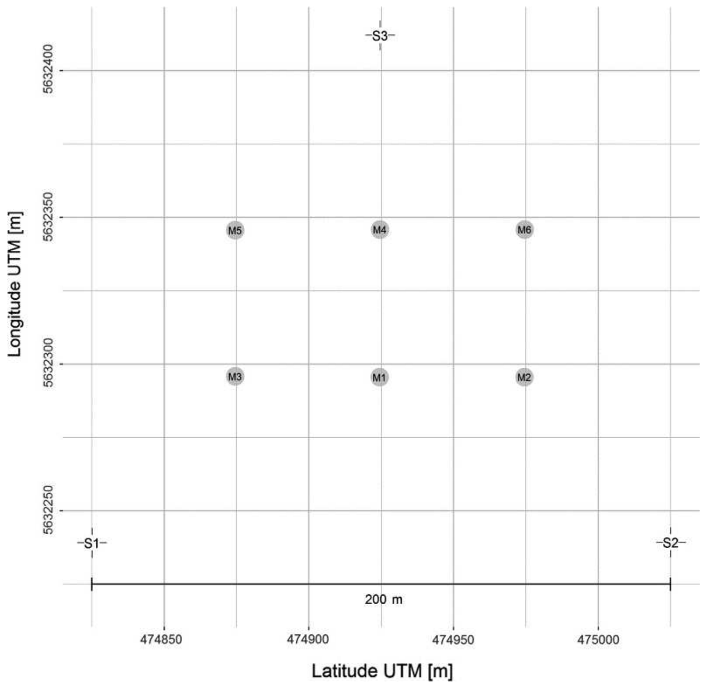


Figure 2.7: Testing scheme. Radio-tracking stations (S1–S3) were placed in an isosceles triangle and a radio tag was placed on each reference position for 2 min (M1–M6)

2.2.2.7 Usability study of forest-dwelling bats in a mixed forest area

Results from an ongoing study that is part of the LOEWE priority program Nature 4.0 – Sensing Biodiversity are briefly presented and discussed to demonstrate the system's capability under field conditions. In 2019, 15 tracking stations were installed in the Marburg Open Forest, the open research and education forest of the University of Marburg, to track bats and songbirds over each breeding season until 2022. Each station is equipped with an array of four HB9CV antennae mounted on 9 m aluminium poles. The stations record movement and body temperature data of tagged bats, which belong to one of four forest-dwelling species (*Nyctalus leisleri*, *Myotis daubentonii*, *Myotis bechsteinii*, *Barbastella barbastellus*). The temperature sensitive tags (V3, Telemetrie-Service Dessau, 0.35 g) vary the time interval between consecutive signals based on the individual's skin temperature.

Exemplary results of bat activity are shown for 26 June 2019. The optimal settings as identified in the accuracy test study were used to triangulate individuals' positions. In order to handle and tag the bats, a special license was granted by the Nature Conservancy Department of Central Hessen (‘Obere Naturschutzbehörde Mittelhessen, Regierungspräsidium Gießen’, v54-19c 2015 h01). Tags were attached to the skin between the scapula with skin adhesive (Manfred Sauer GmbH, Lobbach Germany) and the weight of the attached tags was always <5% of the tagged individual's body mass.

2.2.3 Results

2.2.3.1 Results of the accuracy study

Correction values obtained from local maxima in the calibration curves ranged between 0.07 dB and 2.9 dB with the lowest and highest deviations in maximum received signal strength for stations S3 and S2, respectively (Table 2.1).

Table 2.1: Correction values in dB based on calibration curves obtained in the field

Station	**Correction [dB] 0°**	**Correction [dB] 90°**	**Correction [dB] 180°**	**Correction [dB] 270°**
S1	2.2	1.7	0	0.07
S2	0.26	1.7	0	2.9
S3	0.8	0	0.9	0.98

Thus, calibration had the strongest effect on S2, improving the bearing error from a median of 11.6° to 5.4° (Figure 2.6). Calibration improved the median bearing accuracy by 2° across all stations.

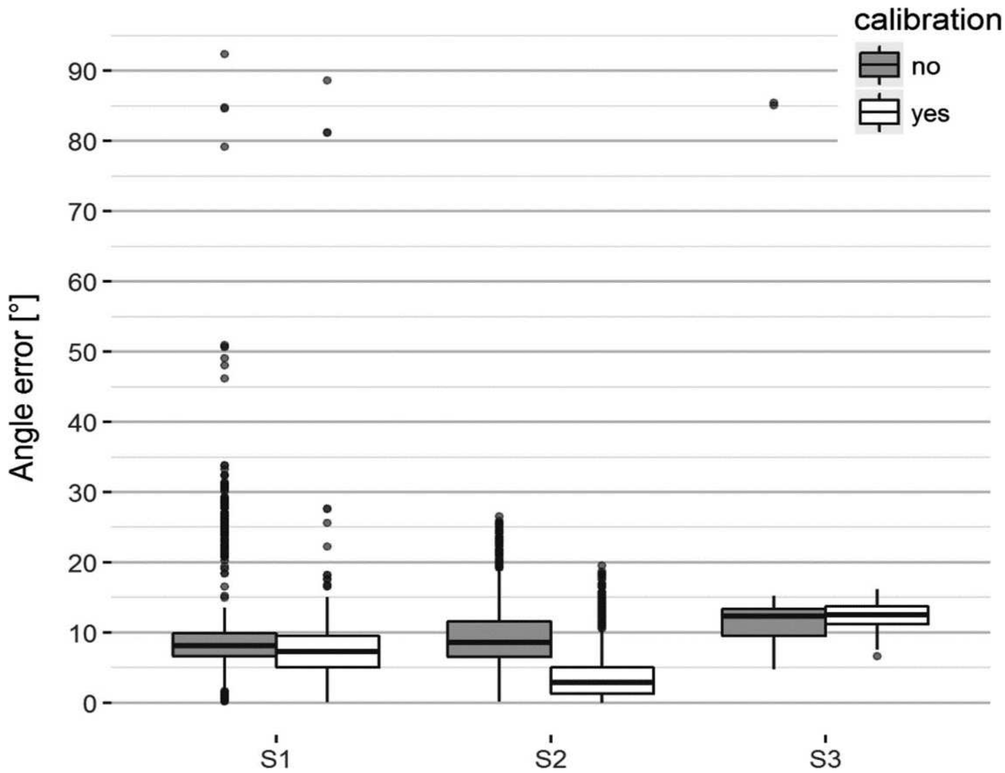


Figure 2.8: Difference in angle error before and after calibration. Calibration substantially reduces the number of points with a high bearing error (outliers in the boxplot)

Bearings calculated based on signals recorded by two antennae deviated from the real angle by 14.9° (median). Bearing error was reduced to 6.8° when more than two antennae received a signal (Figure 2.7).

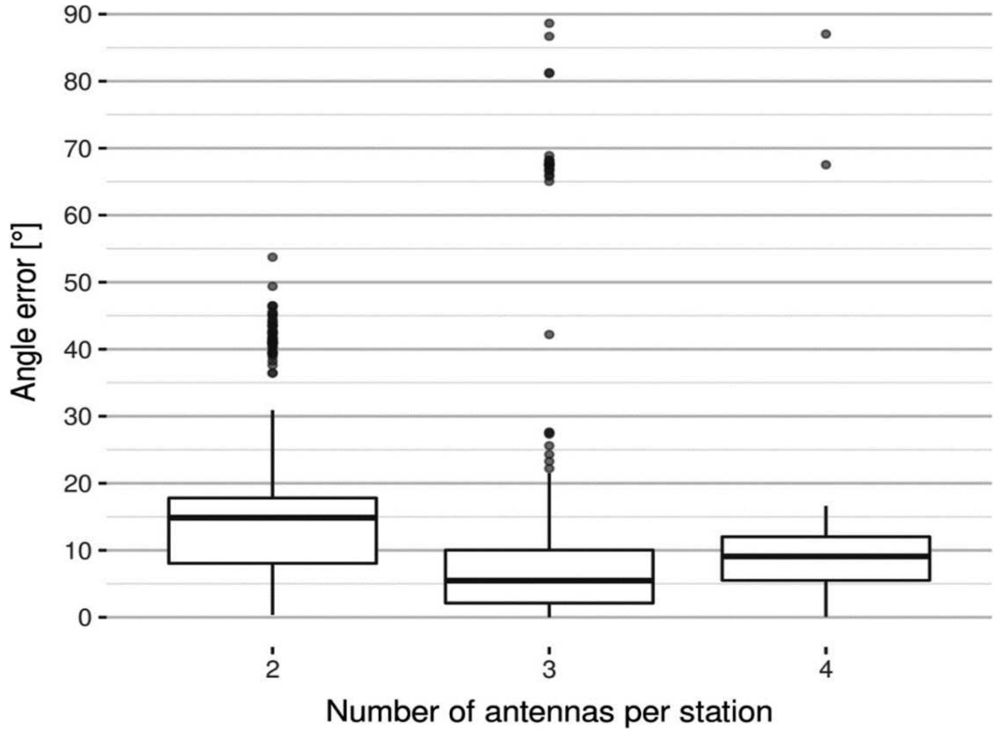


Figure 2.9: Absolute deviation of the bearings from the real angle depending on the number of antennae available. The mean absolute error is 7° with a standard deviation of 6.2°

The position error decreased as the minimum and maximum permissible intersection angles converged towards 90° (Figure 2.8). Minimum and maximum angles of 40° and 140°, respectively, substantially improved results as well as sharply reducing the number of triangulated points. Placing additional limits on the intersection angle steadily reduced the available data.

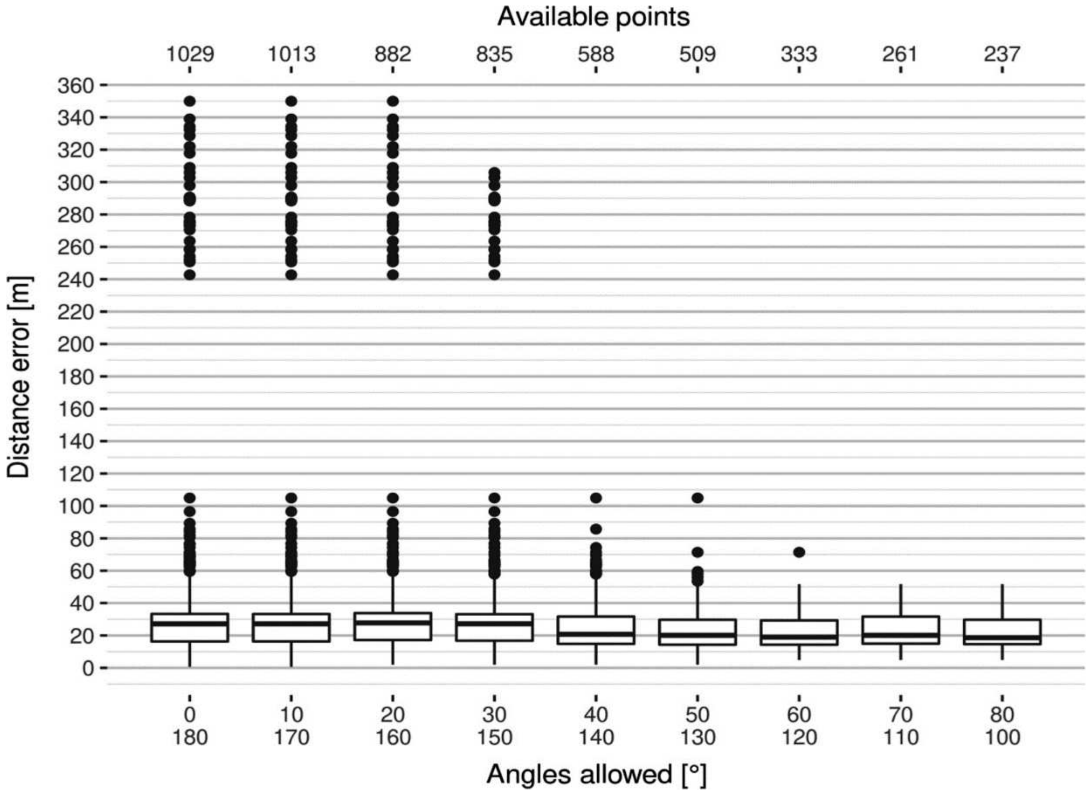


Figure 2.10: Distance error and available locations depending on the allowed cutting angle

Positions were triangulated with calibrated signal strengths and a minimum of three available antennae. Since a substantial number of locations were lost due to restrictions to the intersection angle, we triangulated positions with all intersection angles and with intersection angles restricted to 40–140°. Including all possible intersection angles in the triangulation process results in 673 locations and a mean positioning error of 25 m. The triangulated points scatter in string-shaped patterns around the reference positions (Figure 2.9). Restricting the intersection angles to a minimum of 40° and a maximum of 140° reduces this error to 21 m. However, this results in a substantial loss of triangulated points (292; Figure 2.9) with no points for position M5 (Figure 2.9).

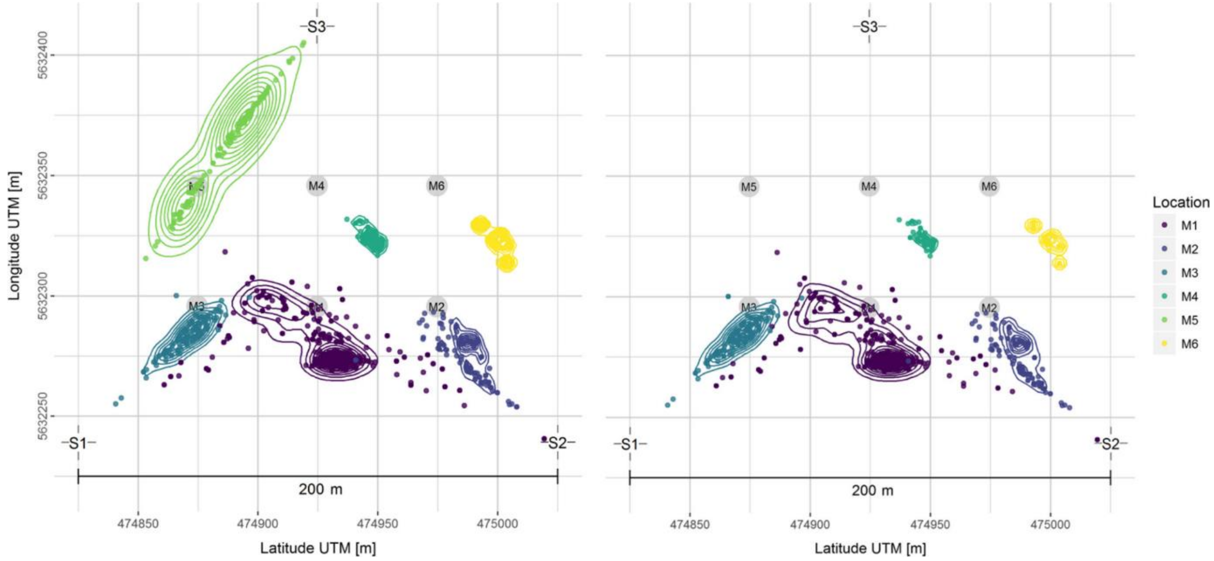


Figure 2.11: Localization points with all cutting angles between two antennae allowed (left) and with cutting angles restricted to 40–140° (right). Isolines represent point density increasing from the outside to the inside

2.2.3.2 Results of the forest usability study

Tracking the movement of *M. bechsteinii* reveals different areas of activity throughout the night (Figure 2.10, left). During 5-min intervals that night (Figure 2.10, right), 301 positions were recorded within an activity area of approximately 50 m2.

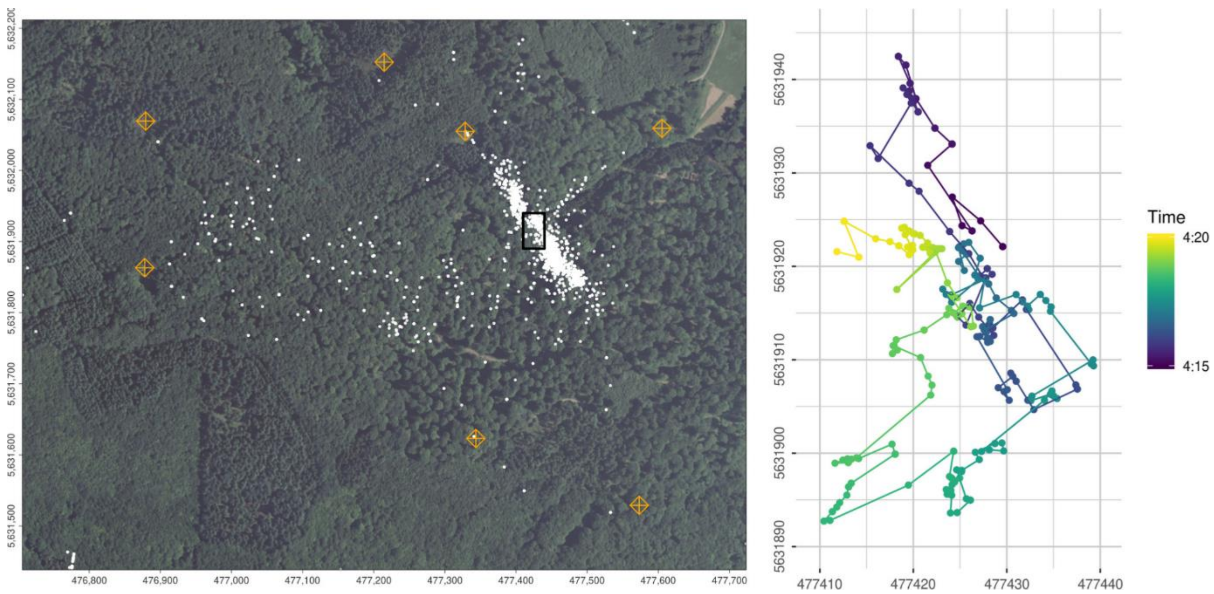


Figure 2.12: Tracking data of a Bechstein's bat recorded on the night of 26 June 2019 (left). Yellow crosses indicate permanent radio-tracking stations. The bounding box (black box) highlights the area of 5 min of relocations shown in detail in the right part of the figure

Body temperature patterns of four different bat species are shown for nocturnal activity and resting in the day roost (Figure 2.11). For the *B. barbastellus* as well as for the *M. daubentonii*, a clear drop of the body temperature of approximately 7°C was recorded shortly before and after sunrise, respectively.

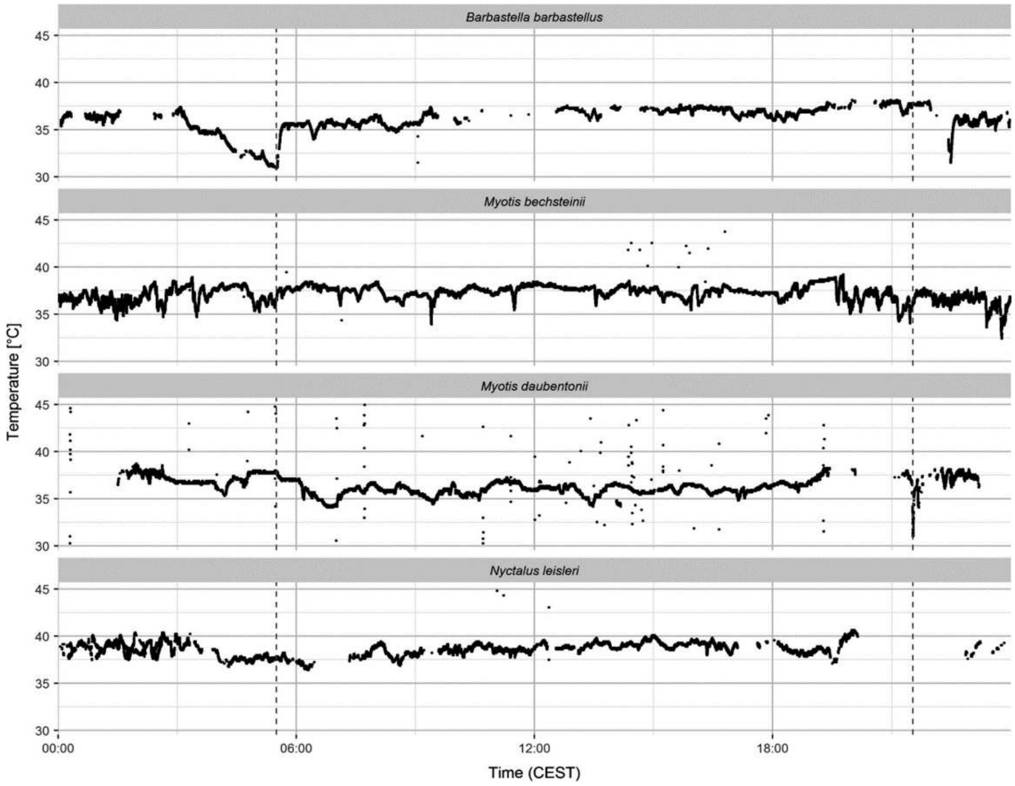


Figure 2.13: 24-hr temperature curves of four different bat species

2.2.4 Discussion

The automatic radio-tracking system presented in this paper incorporates the advantages of lightweight and cost-efficient radio telemetry into a continuous tracking setup. This enhances the number of triangulated positions without manual telemetry and allows analytical techniques previously reserved for fine-scale GPS tracks to be used. These techniques enable researchers to glean important information about different behavioural states of an individual over large trajectories. The exemplary 5-min tracking interval, for example, shows a low displacement in spatial units in relation to the time spent within the area in question, which may be interpreted as an intensive area-restricted search and, thus, foraging behaviour (Knell and Codling 2012).

Overall, the accuracy of the radio-tracking system from the field test compares well to reported manual bearing errors of experienced field workers (Bartolommei, Francucci, and Pezzo 2012). However, this strongly depends on the data processing techniques used. Antenna calibration reduces the bearing error, confirming both the underlying theoretical assumption and the need for calibration to obtain reasonable results. For more precise results, all bearings calculated based on fewer than three available antennae should be excluded from triangulated results. Reducing the intersection angle improves results, yet also reduces the size of the dataset. Since incorrect positioning in our field test appears systematic, errors can be more accurately considered than in manual telemetry and may be further reduced by, for example, field experiments that are able to capture this regularity.

The low-cost solution for automatic radio-tracking presented in this study enables researchers to apply automatic radio-tracking techniques in the field while the open-source hardware and software components allows for active participation in future development. As the principle of calculating bearing is based on physical properties shared by most directional antennae, these algorithms are suitable for triangulating positions with data gathered by other systems such as SensorGnome (https://sensorgnome.org). Further relevant features, such as recording tagged individuals' body temperature have also been implemented and tested.

Continuously measuring animal positions and movement with a long-term antenna setup can greatly contribute to research into animal behaviour. The movement tracks it generates are comparable to those generated by satellite and GPS tracking techniques, even below the canopy in forested areas. This allows researchers to investigate questions related to small-scale habitat and resource utilization, choice of breeding sites or migration and dispersal events in organism groups that movement ecologists cannot yet adequately study due to size restrictions. In this vein, this affordable and easy-to-use automatic radio-tracking system adds a powerful tool to movement ecology research.

Acknowledgements

The first permanent setup of the system was implemented at Marburg Open Forest – the open research and education forest of Marburg University. The research is funded by the Hessen State Ministry for Higher Education, Research and the Arts, Germany, as part of the LOEWE priority project Nature 4.0 – Sensing Biodiversity. Radio-tracking.eu is the outcome of a feasibility study financially supported by the Ministry of the Environment, Climate Protection and the Energy Sector Baden-Württemberg, Germany.

tRackIT OS: Open-source Software for Reliable VHF Wildlife Tracking

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tRackIT OS: Open-source Software for Reliable VHF Wildlife Tracking

Abstract

We present tRackIT OS, open-source software for reliable VHF radio tracking of (small) animals in their wildlife habitat. tRackIT OS is an operating system distribution for tRackIT stations that receive signals emitted by VHF tags mounted on animals and are built from low-cost commodity-off-the-shelf hardware. tRackIT OS provides software components for VHF signal processing, system monitoring, configuration management, and user access. In particular, it records, stores, analyses, and transmits detected VHF signals and their descriptive features, e.g., to calculate bearings of signals emitted by VHF radio tags mounted on animals or to perform animal activity classification. Furthermore, we provide results of an experimental evaluation carried out in the Marburg Open Forest, the research and teaching forest of the University of Marburg, Germany. All components of tRackIT OS are available under a GNU GPL 3.0 open source license at https://github.com/nature40/tRackIT-OS.

2.3.1 Introduction

In an increasingly densely populated and anthropogenically dominated environment, a scientific analysis of the consequences of human-wildlife interaction is essential for developing evidence-based guidelines for conservation (Katzner and Arlettaz 2020). Understanding the impact of altered habitats on the spatial distribution of species (Sawyer et al. 2009), the effects of human infrastructures such as roads (Hothorn et al. 2015; Ascensão et al. 2019), and reasons for increased mortality of endangered species (Lees et al. 2019) is crucial for preserving biodiversity in a crowded world. Movement data of animals generated by recent technological advances support more detailed forms of analysis and insights into the behaviour and ecology of threatened species than ever before (Wyckoff et al. 2018; Walton et al. 2018; Cagnacci et al. 2010).

Wildlife observations can be realized with a variety of technologies. For example, GPS technology can be used to equip animals and record their movements independently of other communication infrastructures. However, size, weight, and battery life constraints prevent the use of GPS for most European songbirds and bats.

Manual radio telemetry is another option for observing small animals. However, it is extremely labor-intensive, limited to a small number of individuals that can be tracked simultaneously (Cohn 1999), and results in spatial and temporal data with poor resolution, which might not be sufficient for meaningful scientific analyses (Montgomery et al. 2010).

Automated radio telemetry systems can minimize many of these disadvantages (Kays et al. 2011; Weiser et al. 2016). In previous work, some of us presented a system based on commodity-off-the-shelf (COTS) hardware for automatic radio tracking of small animals based on Very High Frequency (VHF) tags (Gottwald et al. 2019) as part of the open source project radio-tracking.eu[1]. However, three seasons of long-term stationary operating time of the system in the Marburg Open Forest (i.e. the teaching and research forest of the University of Marburg, Germany) revealed several deficits, such as the lack of failure handling, inadequate interfaces for data transmission and health-state monitoring, and problems with time synchronization of received signals between receivers of the same station and among different stations.

In this paper, we present tRackIT OS, an open-source operating system distribution for reliable VHF radio tracking of small animals. tRackIT OS runs on a tRackIT station; its basic hardware design is due to Gottwald et al. (Gottwald et al. 2019). We developed tRackIT OS to provide new software functionality according to our experiences in studying the movement ecology of both diurnal and nocturnal wildlife with a network of 15 tRackIT stations in densely forested terrain. In particular, we present:

- a novel approach for automated signal detection of VHF radio tracking tags,
- means to provide reliable operation of tRackIT stations under harsh conditions,
- efficient live data transmission for monitoring data and detected signals,
- a novel web-based user interface for intuitive configuration of tRackIT stations,
- a comparative evaluation of tRackIT OS compared to the state-of-the-art.

The rest of the paper is organised as follows. Section 2 discusses related work. Section 3 discusses requirements, design decisions and implementation details, followed by experimental results in Section 4. Section 5 concludes the paper and outlines areas of future work.

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[1] https://radio-tracking.eu

2.3.2 Related Work

Ripperger et al. present a comprehensive overview of existing systems for localizing small animals using different technologies (Ripperger et al. 2020). The most recent projects on automated VHF transmitter tracking are ARTS (Kays et al. 2011), Atlas (Weiser et al. 2016), and Motus (also called SensorGnome) (Taylor et al. 2017).

ARTS consisted of towers with a height of 40 meters and top-mounted antenna arrays (Kays et al. 2011), but the system was taken down in 2010 and replaced by camera traps and GPS transmitters. ARTS was able to determine the position of a tagged individual by triangulation with an spatial accuracy of 50 meters, but rotating through channels with different frequencies reduces the time span in which each individual can be observed. tRackIT supports more detailed observations of movements using a higher number of stations at lower cost and less effort in construction.

The Atlas project achieves great spatial accuracy by using the time difference of arrival (TDOA) method for direction estimates as seen from the receiver, while costs for the developed tags are low (Weiser et al. 2016). However, implementation of the receiving stations is quite expensive, a fact that probably explains why the system is only deployed in three areas in the Netherlands, England, and Northern Israel. tRackIT achieves comparable results with stations built from commodity off the shelf hardware at a lower price point.

Motus[2] is a globally operating network of VHF receiver stations hosted by different collaborators and supporting researchers (Taylor et al. 2017). Despite its open source character, an implementation of Motus at US$ 3000 for a single SensorGnome[3] receiver with three 9-element Yagi antennas, and US$ 7500 for a Lotek SRX800 receiver station with four 9-element Yagi antennas is costly (Lenske and Nocera 2018), leading to a trade-off between spatial resolution and coverage. By default, the implemented radio receiver listens at a single center frequency and can detect pulses from tags in a narrow band of ±24 kHz around its center frequency. This limits the number of distinguishable frequencies, i.e., the number of detectable individuals, substantially. Motus has delivered great insights into the ecology of different species in more than 120 research projects (Taylor et al. 2017), but investigating fine-grained spatial movements by triangulation is not supported by the system. The wide frequency band that can be used by tRackIT supports both fine-grained temporal resolutions and observations of many individuals.

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[2] Motus Wildlife Tracking System: https://motus.org
[3] SensorGnome Project: https://sensorgnome.org

2.3.3 tRackIT OS

A tRackIT-system consists of (a) VHF radio tags mounted on animals, (b) tRackIT stations for receiving signals emitted by VHF tags, (c) tRackIT OS running on tRackIT stations for detecting and matching signals received on multiple antennas, (d) tRackIT servers for collecting and presenting data transmitted from tRackIT stations, and (e) tRackIT analytics modules for deriving ecological knowledge from the collected data.

In this section, we present design and implementation issues of tRackIT OS, the operating system distribution for tRackIT stations.

2.3.3.1 Requirements

Our experiences from three seasons of field work have indicated that automatic telemetry can only be a useful substitute of its manual counterpart if certain requirements are met:

1. Low entry barrier. To make automatic radio telemetry accessible to the widest possible user community, both hardware and software as well as data processing and analysis must be conveniently accessible, easy to use, and inexpensive.
2. Reliability. The used equipment must reliably record signals originating from VHF transmitters and minimize the amount of interference. Any component failures caused by adverse conditions, such as unstable power supplies, fluctuating temperatures, and hardware-based failures should be detected and handled automatically.
3. Data availability. In many application areas, like mortality studies[4], fast data availability is highly important. Thus, direct data transmission from the field with the shortest possible delay between recording and transmission is desirable.

2.3.3.2 tRackIT Station

To deploy an operational installation in the field, a tRackIT station is equipped with directional antennas in the four cardinal directions, a solar panel, and a battery box. The basic hardware design is due to Gottwald et al. (Gottwald et al. 2019). We have slightly adapted the hardware by including an active USB hub, a better LTE modem, and a LoRa

[4] https://www.wildanimalinitiative.org/blog/cause-of-death-2

(Long Range Wireless Radio Frequency Technology[5]) expansion board (LoRa HAT), as shown in Figure 2.12.

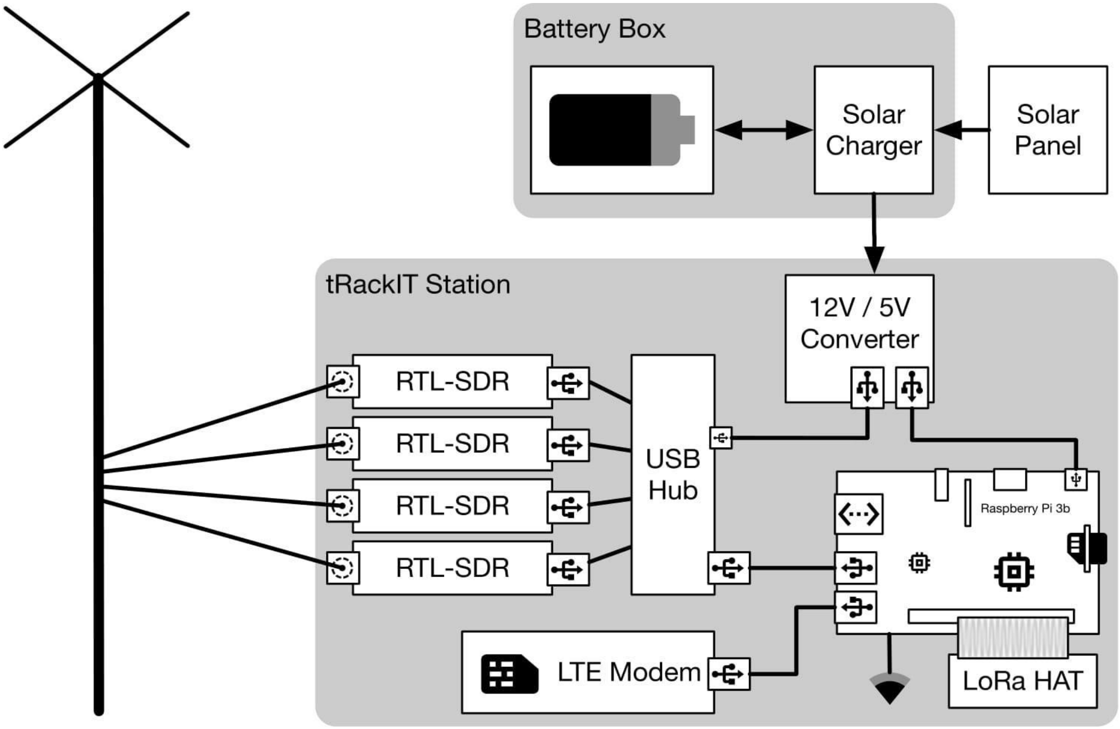


Figure 2.14: The hardware components of a tRackIT station

The 'brain' of a tRackIT station is a Raspberry Pi 3 Model B that consists of a quad-core 1.2 GHz ARM-Cortex-A53 and 1 GB of RAM. It offers various input/output options, including Wi-Fi and 4 USB ports. The system is powered through a 5V USB port and is capable of powering connected USB devices. The four directional antennas are connected to four software-defined radios (SDR) (Nooelec NESDR SMArt v4) for signal analysis. Since these SDRs require more power than provided by the Raspberry Pi, an active 4-port USB hub (Anker 4-port Ultra Slim USB 3.0 Data Hub, A7518) is used to connect the devices. An LTE modem (Huawei E3372H) and a local prepaid data plan is used to establish a mobile Internet connection. The battery box provides a 12 V source that is converted using a step down converter rated for 2 × 2.4 A at 5 V. For tRackIT stations relying on LoRa for data publishing, a Dragino SX127X GPS HAT[6] is used. For receiving and forwarding tRackIT stations, the Dragino PG1301 LoRa Concentrator is used[7]. The basic hardware of a tRackIT station costs a total of about 200 €, consisting of 35 € for the

[5] Semtech: https://www.semtech.com/lora/
[6] Dragino SX127X: https://www.dragino.com/products/lora/item/106-lora-gps-hat.html
[7] Dragino PG1301: https://www.dragino.com/products/lora/item/149-lora-gps-hat.html

Raspberry Pi 3B+, . 4 × 35 € for the Nooelec SDRs, 15 € for the active USB hub, and 10 € for the power supply unit. The optional communication modules cost 50 € in the case of the Huawei LTE modem and/or 35 € (LoRa HAT) / 110 € (LoRa Concentrator) for the LoRa publish / receive upgrade.

2.3.3.3 tRackIT OS Components

The operating system (OS) plays a crucial role in the reliable autonomous operation of the presented hardware. We developed a custom distribution of the Raspberry Pi OS, called tRackIT OS. The primary task of tRackIT OS is to execute a signal detection module, called pyradiotracking, in a reliable manner. The secondary task is to interface with users (a) interactively while setting up the station, and (b) continuously during autonomous operation for extended monitoring. tRackIT OS is built using PIMOD (Höchst, Penning, et al. 2020), which allows configuration of single-board computer system images in a reproducible manner. The resources required to build tRackIT OS as well as the OS image itself are released under a GPL 3.0 license[8].

In Figure 2.13, the main software components of tRackIT OS are presented. Station-initiated communication is handled using the Message Queuing Telemetry Transport (MQTT) protocol, with mosquitto as an MQTT client and server implementation (Light 2017) for message distribution. It is configured such that incoming messages are forwarded to remote MQTT brokers for further processing. These brokers are also responsible for detecting and resolving connection failures.

[8] tRackIT OS, available online https://github.com/Nature40/tRackIT-OS

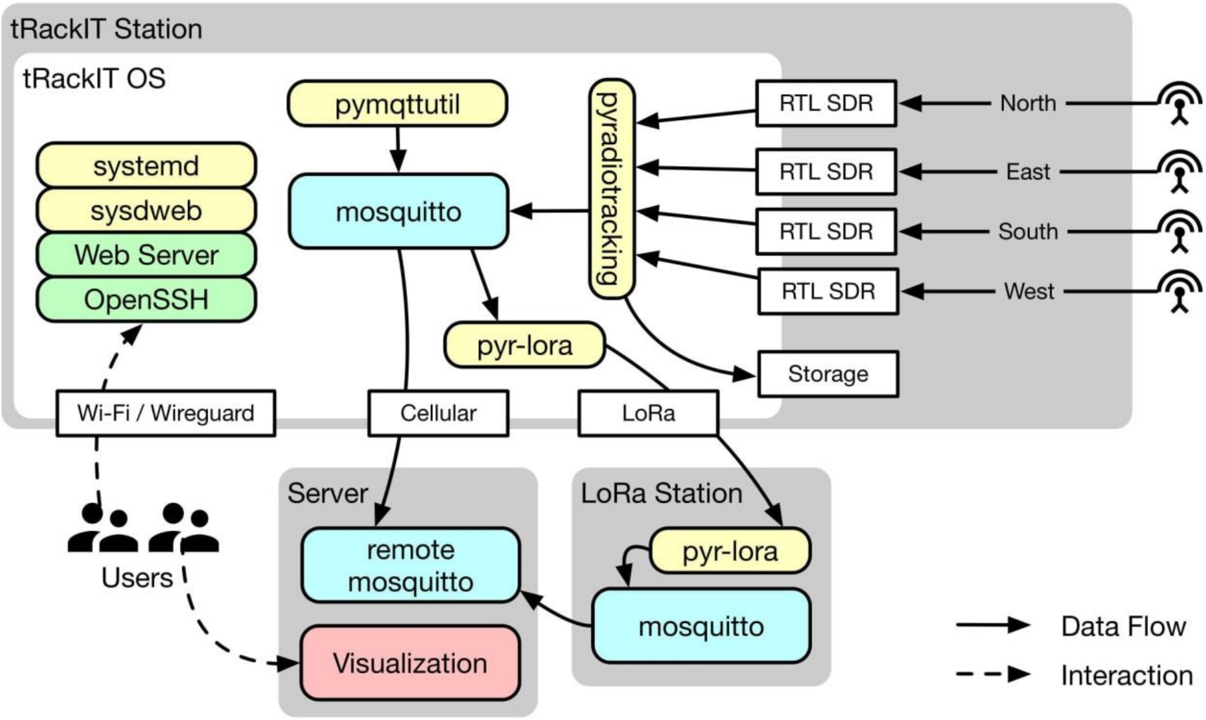


Figure 2.15: Overview of the main software components of a tRackIT OS distribution

The core software component for signal detection is called *pyradiotracking*. The component reads samples from all four SDRs, as well as detects, filters, and matches signals of VHF tags. Detected signals are saved to local storage, displayed via a custom web user interface, and published to a local message bus that is responsible for data distribution. Section 3.4 discusses the implementation details of *pyradiotracking*.

For system monitoring, we implemented a custom tool called pymqttutil in the Python programming language. It is released under a GPL 3.0 license[9]. The tool executes configurable Python statements in a fixed schedule and publishes the corresponding results via MQTT. It is configured such that relevant system metrics are published in a 5 minute interval, i.e., temperature, system uptime, system load, memory usage, CPU frequency, network addresses, storage utilization, and cellular data usage.

All services are managed by systemd. The WebUI sysdweb[10] for systemd is configured to allow easy log access and service control for (mobile) users. The Caddy web

[9] pymqttutil, available online: https://github.com/Nature40/pymqttutil
[10] sysdweb, available online: https://github.com/Nature40/sysdweb

server is used to provide convenient access to the local storage, pyradiotracking and sysdweb. Finally, OpenSSH provides direct system access for local and remote users. To allow secure remote access, wireguard is used as a virtual private network (VPN).

2.3.3.4 Signal Detection

The signal detection algorithm is implemented in the pyradiotracking Python package, which is released under a GPL 3.0 license[11]. In Figure 2.14, the stages of signal processing are presented in a block diagram. First, spectrograms of the incoming IQ samples are created, which are used to detect signals. The detected signals are then filtered for shadow signals of lower power in neighboring frequencies and sent to a central signal queue. The detected signals of multiple antennas are matched and written to a local file, published to the MQTT message bus, and visualized in the local dashboard.

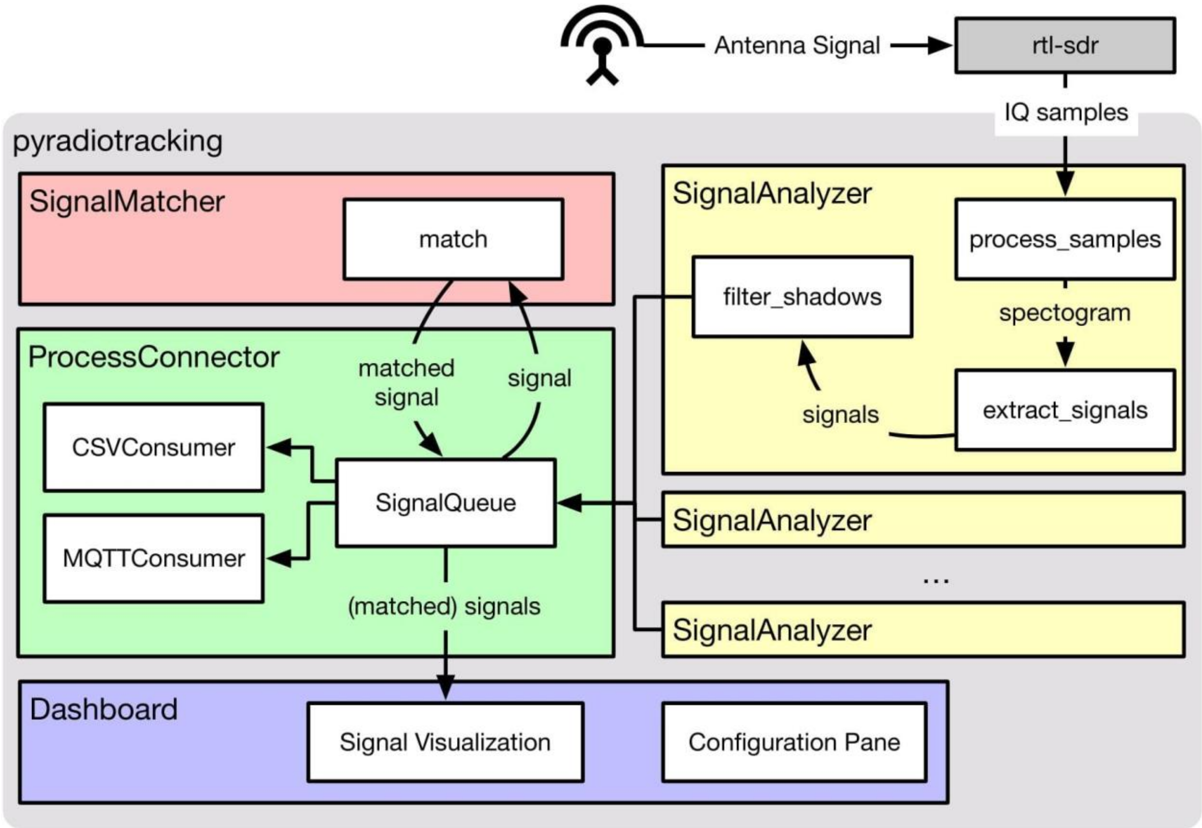


Figure 2.16: Signal analysis stages implemented in pyradiotracking

To illustrate how the different stages work, data of the length of one second is used as an example. An SDR is configured such that a center frequency of 150.150 MHz, a sample rate of 300 kHz, and a fixed gain of 49.6 dB are used. A test tag with the frequency

[11] pyradiotracking, available online: https://github.com/Nature40/pyradiotracking

of 150.172 MHz and a signal duration of 40 ms was placed near to the receiving antenna. In Figures 2.15, 2.16, and 2.17, three stages of signal processing are visualized.

Figure 2.15 shows the raw IQ samples received by the SDR. Following the example configuration described above, there are 300,000 samples, hence 600 kilobyte of data collected in one second. In the time interval of $t_0 = 0.45\ s$ to $t_1 = 0.49\ s$, the IQ samples contain high values, which appear as a rectangle in the visualization. This rather sharp rectangle indicates that the gain value is set too high and the signal is clipping. When setting up stations for regular operation, the gain value must be chosen such that a good compromise of gain and clipping is achieved.

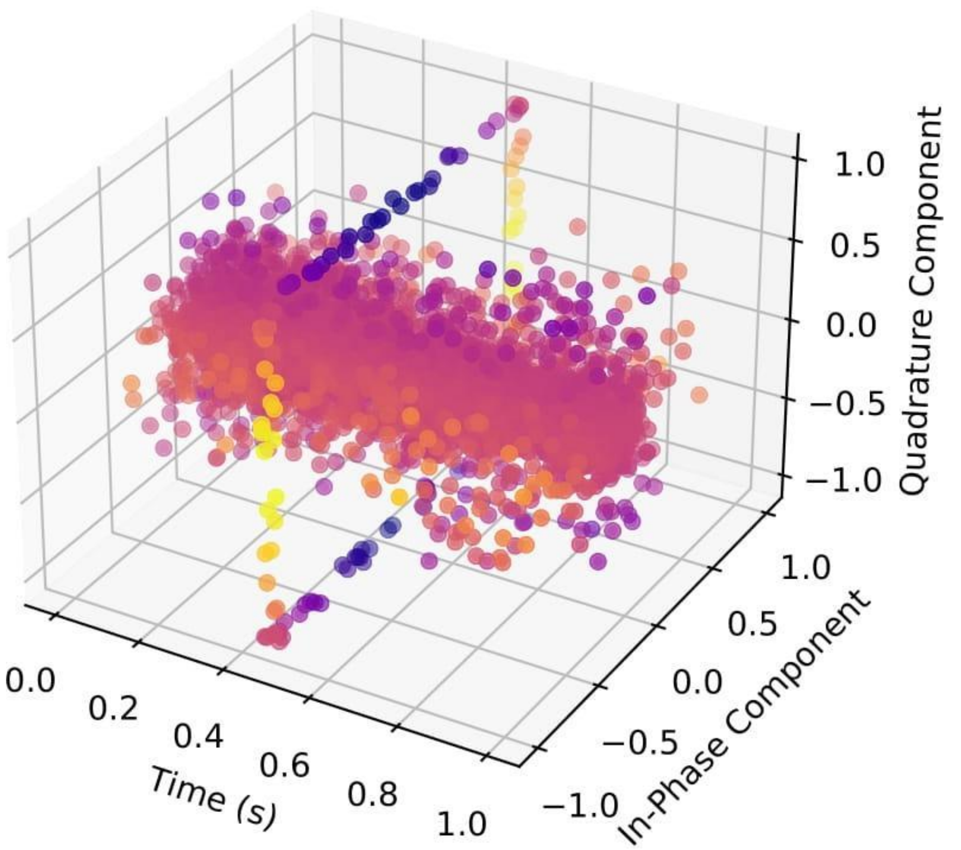


Figure 2.17: IQ samples of one second, as received by RTL-SDR

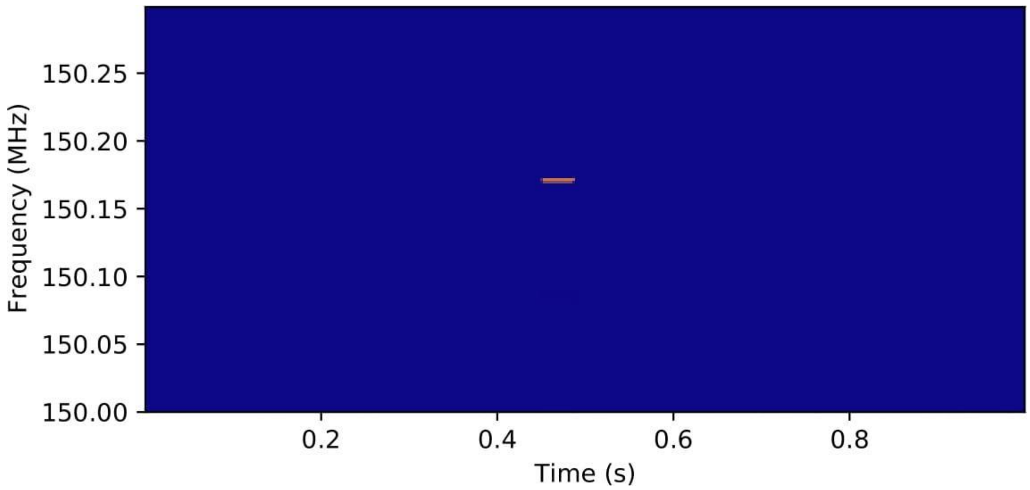


Figure 2.18: Power spectral density (PSD) of samples computed via Short-time Fourier Transform (STFT).

To detect single signals from the received data, a spectrogram is computed and processed further. This is achieved by applying consecutive Short-time Fourier Transforms (STFT) (Allen 1977) to the data. Figure 2.16 shows the spectrogram computed from the previously presented example data. The STFTs are computed with 256 samples per Fast Fourier Transform (FFT) and no overlapping samples. The Hamming window function is applied to smoothen discontinuities at the start and the end of the processed FFT. In this configuration, the bandwidth of 300 kHz is divided into 256 bands and a frequency resolution of 1,171 kHz, to achieve a time resolution of 1.0 $s/1,171 = 0.853\ ms$.

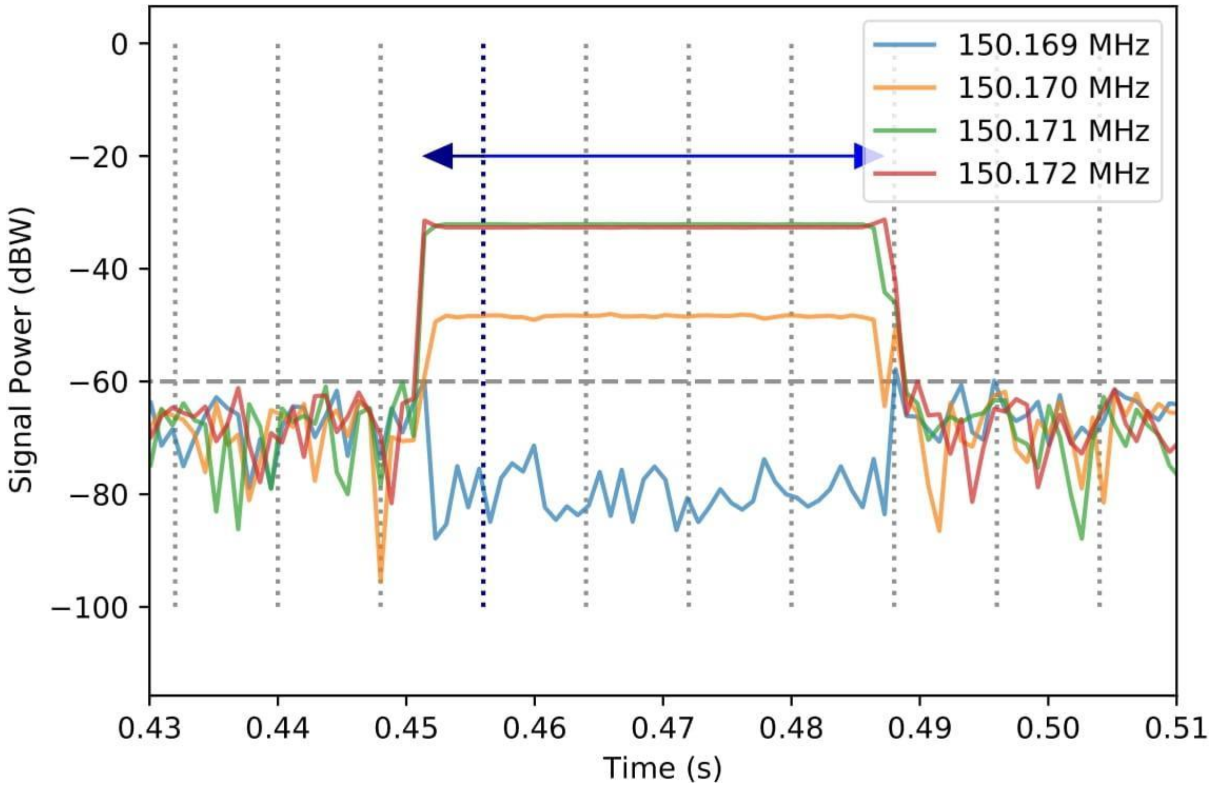


Figure 2.19: Power spectral densities (PSDs) of selected frequencies, minimal signal power threshold, and signal power sampling points.

In Figure 2.17, signal detection on individual frequencies is visualized. The signal power (dBW) in the logarithmic scale is plotted for four example frequencies near the test sender's frequency, and the signal emitted by the test sender can be observed in three of those. The gray dashed horizontal line indicates the configured signal power threshold of -60 dBW. The gray dotted vertical lines show scan points used for initial signal detection. The blue arrow marks the total detected signal length. Signal detection is achieved by (a) iterating through all frequencies and (b) iterating through time using scan points placed according to the minimal detectable signal duration of 8 ms in our example. The signal-to-noise ratio (SNR) is calculated using the ratio of the current power and the average signal power of this frequency. If signal power and SNR at the scan points are above the configured thresholds, a potential signal is detected. The scan is then continued by evaluating the thresholds for all neighboring values until the thresholds are undershot, indicated by the blue arrows. If the duration of the detected signal is within the set limits, further complementary features are computed and added to a list for further processing.

After all signals of a spectrogram are extracted, shadow filtering is performed. We define a shadow signal as a signal that matches another signal in duration and time, but has a lower detected power. In the example of Figure 2.17, the signals detected at 150.170 MHz and 150.172 MHz would be shadow signals of the 150.171 MHz signal. The shadow signals are removed and the detected primary signals are added and written to disk, published via MQTT and sent to pyradiotracking's main process for signal matching and data presentation.

To improve reliability, a direct control component is introduced. The librtlsdr library used to retrieve data from an SDR works in such a way that as soon as requested data is available, a callback method is called. If the system load is too high and the callback method takes longer than the acquisition of the next samples, individual samples are omitted. Hardware and library-specific errors may lead to no callbacks at all. The first problem is monitored by comparing the actual received samples with the expected number of samples using the system clock. In this way, dropped samples can be detected, even accumulated over longer periods of time. The second problem is solved by (re-)setting a periodic alarm, comparable to a dead man's switch. If the callback method is not called in time, an alarm is triggered. This terminates the analysis process, which is then restarted by pyradiotracking's main process.

2.3.3.5 Signal Matching

The detected and filtered signals of multiple antennas are consumed by the signal matcher, which works as follows. In a list, all currently active signal groups are held. When a new signal is detected, it is compared to each of the active signal groups in time, duration, and frequency. The SDR devices used in the project do not work synchronously and use individual quartz crystals as their clock sources, hence time and frequency mismatches are likely to happen. If all parameters of an active signal group are within the configured thresholds, the signal is added to the corresponding group. If no corresponding group is found, a new active signal group with this signal is created and added to the list. After a certain timeout, the active signal groups are removed from the list and the key features are written to disk and published.

2.3.3.6 Data Publishing

Detected signals are published directly to disk in CSV format and via MQTT in the CBOR format, which is a binary format and introduces smaller overheads compared to text-based formats. The MQTT broker running on a tRackIT station can be configured to forward published signals to other brokers, such as a central server via a cellular network or other IP-based networks.

Table 2.2: tRackIT station's LoRa matched signal payload: fields, accuracy, and sizes.

Field	Accuracy	Size (bit)
Time	ms of current min	16
Frequency	offset to 150 MHz in kHz	9
Duration	ms	6
Signal Availability	flags	4
Signals	3-decimals	[1 − 4] × 17
		52 - 103

In addition to this IP-based data publishing, LoRa can be used to publish signals. LoRa is a physical layer protocol based on chirp spread spectrum (CSS) modulation, that is robust against channel noise, multi-path fading, and the Doppler effect. This allows transmission ranges of a few kilometers in urban environments and up to 15 kilometers in rural areas, with minimal power requirements but also only low data rates between 300 bps and 50 kbps (Mdhaffar et al. 2017; Petäjäjärvi et al. 2017; Höchst, Baumgärtner, et al. 2020).

The LoRa publishing service of tRackIT OS receives signals through the local MQTT broker, converts the data in a custom data-saving binary format, and sends it via LoRa. Table 2.2 shows the fields used for a matched signal's payload, including accuracy and required size in bits. A matched signal contains a minimum of one and a maximum of four signals, depending on the number of antennas that received the signal, hence the final payload size is 52 up to 103 bits. Zeros are appended to the payload to reach the required byte boundaries, resulting in messages of 7, 9, 11, and 13 bytes, depending on the number of the contained matched signals. Compared to the already compact representation in CBOR of a 4-component matched signal (56 bytes + overhead), a reduction of up to 77% is achieved (13 bytes). In the most robust LoRa settings (SF:12, BW:250 kHz, CR:4/8), such a shortened message would require 594 ms Time-on-Air (ToA) (using Implicit Header mode with a 1-byte sender ID, the total length of the packet is 14 bytes). Following the duty cycle regulation of a maximum utilization of 1% (10%) per band, a message could be sent every 59 (5.9) seconds. While these settings do not allow continuous monitoring of individuals, sparse reporting of single observations are still of value, when trying to detect tags fallen off or with empty batteries. For stations in closer physical proximity to the receiving gateway, less robust settings may be chosen. Using a less robust LoRa setting (SF:8, BW:250 kHz, CR:4/8), the ToA drops down to 45.5 ms, allowing messages to be sent in an interval of 4.6 (0.46) seconds. From previous measurements in the Marburg Open Forest, signals could be reliably transmitted over 600 meters using this setting.

2.3.4 Experimental Evaluation

In this section, we evaluate tRackIT OS in benchmarking scenarios and in field experiments. The data of all experiments is publicly available at https://github.com/Nature40/ hoechst2021tRackIT-eval.

2.3.4.1 Experimental Scenario

To evaluate tRackIT OS in a realistic manner, we use a system setup in the Marburg Open Forest, consisting of 15 tRackIT stations; 5 of them are used in our evaluation described below. The experiments are carried out twice: (a) with the most recent tRackIT OS 0.7.0 and (b) using the most recent stable operating system version of the radio-tracking.eu[12] project (Gottwald et al. 2019), called paur 4.2. We activated a test tag and carried it around in the area of the selected tRackIT stations together with a GPS receiver to receive ground truth data. The experiment took place over the course of 0:51:10 h with a VHF sender of 600µW power, 20 ms duration and an interval of one signal per second, which results in 3,193 sent signals.

[12] https://radio-tracking.eu

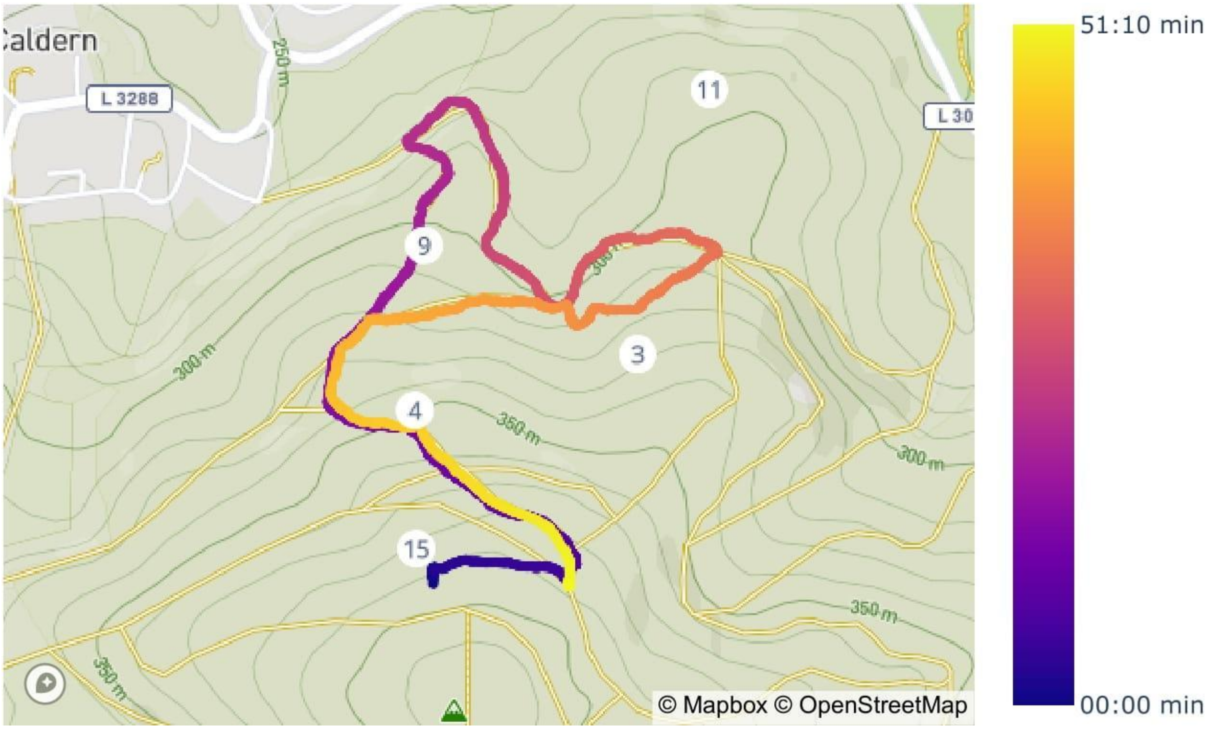


Figure 2.20: GPS trace of the experimental evaluation track and the corresponding tRackIT stations.

In Figure 2.18, the GPS trace of the conducted experiment is presented; stations are marked by the white circles, and the trace is colored to indicate the time component of the experiment. Our observations using paur in two seasons of 2019 and 2020 indicated high numbers of falsely detected signals. We were not able to distinguish between true and false positives through the information available after signal detection. Thus, we used a power signal threshold. The paur experiments conducted in this paper showed the same low precision, hence all detected signals with a power lower than -78 dBW were removed for further processing. Using tRackIT OS, this threshold is not required, since we observed very low numbers of falsely detected signals.

2.3.4.2 Signal Delay

A second observation from our previous field seasons in 2019 and 2020 is a delay in signal detection using paur in the order of seconds to minutes. In Figure 2.19, an example of observed signal delay is visualized. The dots show the received signal strength measured on multiple antennas of the same tRackIT station. Every antenna received a series of signals with low variance in signal strength that appear to be a straight line, indicating that the tag is not moving. However, these straight lines on the individual receivers are offset in time from each other, which makes further processing of the data difficult and and leads to worse to unusable bearing calculation. In the experiments of this paper, we measured a delay in signal detection of 8 seconds in paur and no recognizable delay in tRackIT OS.

Figure 2.21: Example of signal delay among different receivers observed in the 2020 field season using paur.

2.3.4.3 Signal Detection

In the tRackIT OS experiments, the selected five tRackIT stations detected 30,507 signals, each on potentially four antennas, resulting in an average of 1,525 signals (47.8%) detected per antenna. Signal detection depends on various factors, such as geographical and topographical conditions, the orientation of the antenna, the height of the transmitter above the ground, air humidity, and forest cover. Figure 2.20 shows the numbers of detected signals by station and antenna. Due to the positioning of the stations, the orientation of the antennas, and the selected test area, some of the antennas receive only a very small amount, others a large amount of the test signals. On the north antenna of station 11, only 95 (3.0%) signals could be detected, while 2,611 (81.8%) signals were detected on the south antenna of station 9.

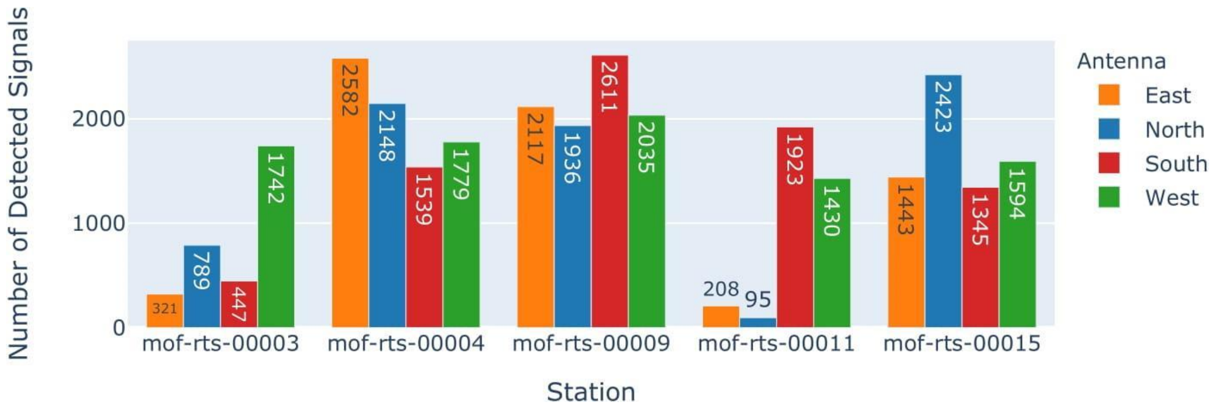


Figure 2.22; Detected signals on tRackIT stations in the experimental scenario.

In addition to this quantitative analysis of signal detection, we evaluated the distances between the test tag and the tRackIT stations. Figure 2.21 shows the distance of the tag and stations measured via GPS and the power of the detected signal. While most stations can detect signals at distances of up to 400 meters, stations 4 and 11 detect signals up to 800 meters away. While the correlation of signal strength and measured distance is straightforward, a high variance can be observed from the data and signal strength alone, hence this is not a suitable estimator for distance in the presented experiment. Initially, the overall performance of the two systems appears comparable, especially for signals with high signal strength. While paur received 2,728 signals usable for bearing calculations, tRackIT OS received 4,438 such signals, an increase of 62.7%, when applying the same -78 dBW threshold. In addition, tRackIT OS received 1,108 signals of lower signal strength, which corresponds to an effective increase of 103.3% compared to paur.

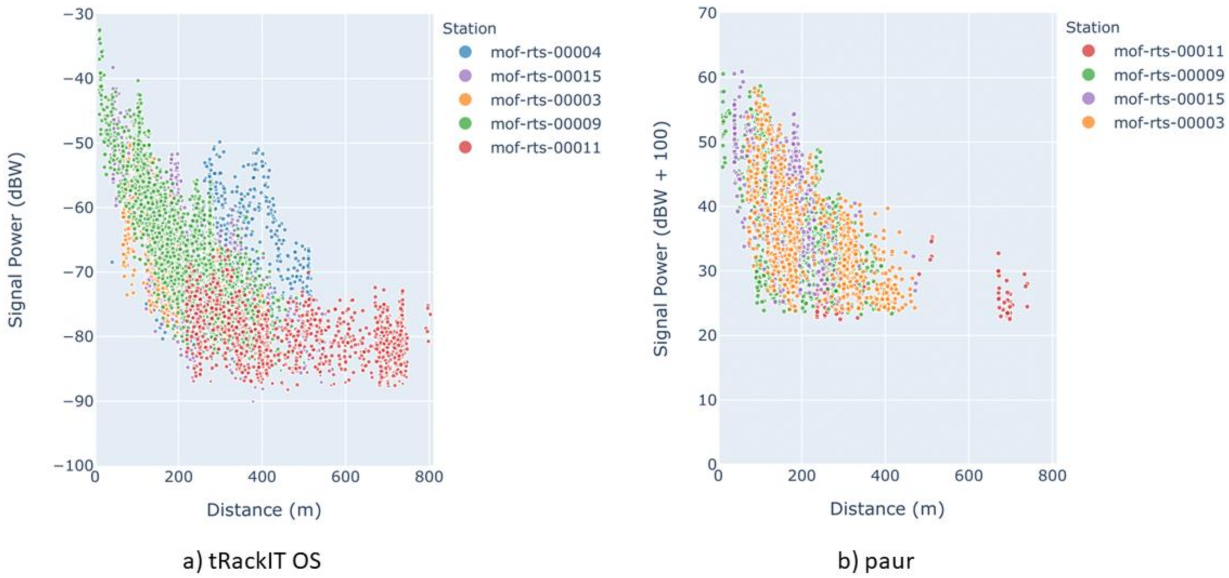
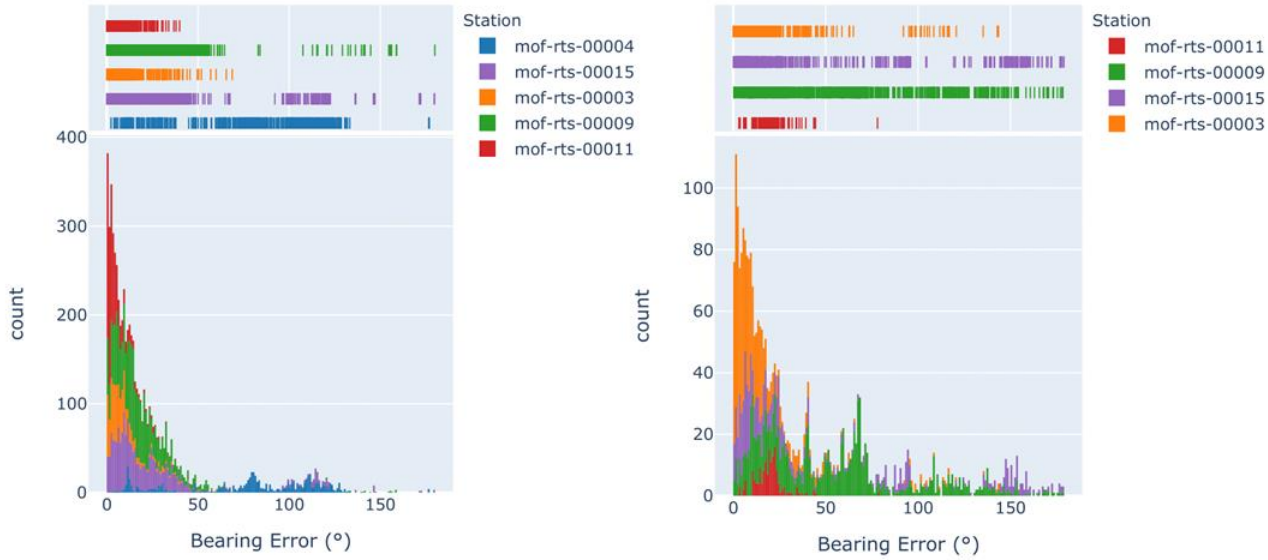


Figure 2.23: Signal power and distance to a receiving station.

2.3.4.4 Bearing Calculation

To reach the goal of signal triangulation, signals detected on multiple antennas of a station are used to calculate bearings. We use the method proposed by Gottwald et al. (Gottwald et al. 2019) to produce comparable results for our bearing calculation. First, the pair of neighboring antennas with the highest and second highest signal strength are selected (sl , sr) and the relative gain difference δg is computed using the maximum signal strength difference δm: g = $sl - sr \ \delta m$. Second, the signal strength is used to calculate the bearing between the antennas following the formula derived from the cosine theorem: ω = π 90 × $arccos(\delta g)$.



a) tRackIT OS

b) paur

Figure 2.24: Histogram of bearing errors.

Figure 2.22 shows a histogram of bearing errors in tRackIT OS and paur. Due to an error on station 4 which was not resolved automatically, signal detection failed on this station in the paur experiment run, hence no data is presented in the histogram. While tRackIT OS has a mean bearing error of 23.7° and a standard deviation of 30.7°, paur not only has a lower total bearing count, but also results in 38.9° mean bearing error with 42.6° standard deviation. These results indicate that tRackIT OS is superior to paur that represents the current state of the art in this field.

2.3.4.5 Power Requirements

To operate stations autonomously and to monitor and transmit data, a stable power supply is necessary. To get realistic values for the required power, we measured a tRackIT station at the 12 volts input using a Monsoon High Voltage Power Monitor15 .

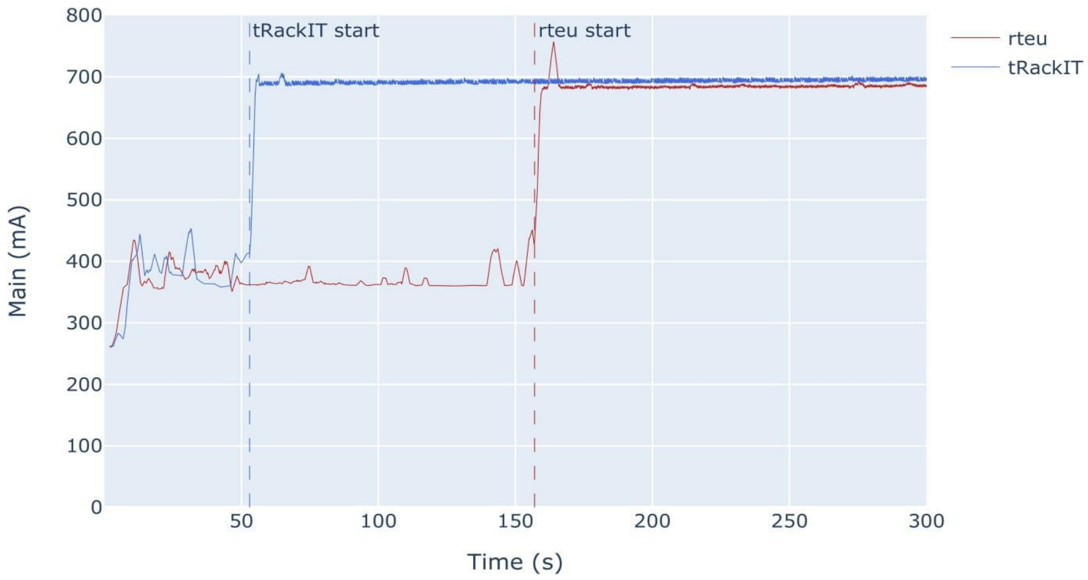


Figure 2.25: Power measurements of tRackIT OS and paur in default settings.

Figure 2.23 shows the power demands of paur and tRackIT OS. In contrast to tRackIT OS, paur does not start signal detection automatically. After all SDRs and signal analysis threads are running, tRackIT OS consumes an average of 8.23 W (684 mA), while paur consumes an average of 8.03 W (667 mA), which is an overhead of 2.55%. We also carried out experiments with varying sample rates (225 kHz – 300 kHz), but did not observe varying power demands. The systems used in the Marburg Open Forest use 12 V batteries with a capacity of 120 Ah (1440 Wh) of which only 80% should be used to limit wear, which allows a maximum theoretical runtime of 140 hours, or roughly 5.5 days. To allow a continuous operation, a 300 Watts peak solar panel is connected via a solar charger that even works during cloud cover. The presented results show only a slight increase in power consumption of tRackIT OS compared to paur, i.e., tRackIT OS meets the power requirements for continuous operation of the system.

2.3.5 Conclusion

We presented tRackIT OS, open-source software for reliable VHF radio tracking of small animals in their wildlife habitat. tRackIT OS is an operating system distribution for tRackIT stations that receive signals emitted by VHF tags mounted on animals. tRackIT OS encompasses components for VHF signal processing, system monitoring, configuration management, and user access.

We evaluated and compared tRackIT OS against a previous operating system distribution (called paur), in an experimental field evaluation carried out in the Marburg

Open Forest. Our experimental results showed that compared to paur, tRackIT OS (a) enables reliable VHF signal detection for bearing calculation, (b) increases the number of usable signals by 103.3%, (c) improves the mean bearing calculation error from 38.9° to 23.7°, and (d) introduces only a slight overhead in power consumption of 2.55% or 0.2 W. tRackIT has the potential to substantially improve the quality of habitat usage studies and/or environmental assessments in the context of anthropogenic interventions in the environment, while massively reducing the time required for field work.

There are several areas for future work. For example, calculating exact bearings can be challenging, since signals are affected by multiple factors, such as vegetation, topology of the surrounding area, humidity, and rainfall. While bearings can be directly calculated based on a simple model, higher quality can be achieved by using data of multiple stations and further context information, such as a topology model and/or a calibration for the specific area of operation. Furthermore, it is quite challenging to transmit all detected signals under the given bandwidth limitations of the LoRa protocol. A coordinated selection and transmission approach for detected signals should be developed to increase the efficiency of stations connected via LoRa. Finally, the continuous preparation and further processing of the collected data is the next major task in creating a user-friendly and widely applicable animal tracking system for generating ecological knowledge.

Acknowledgements

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The BatRack: An open-source multi-sensor device for wildlife research

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The BatRack: An open-source multi-sensor device for wildlife research

Abstract

1. Bats represent a highly diverse group of mammals and are essential for ecosystem functioning. However, knowledge about their behaviour, ecology and conservation status is limited. Direct observation of marked individuals (commonly applied to birds) is not possible for bats due to their small size, rapid movement and nocturnal lifestyle, while neither popular observation methods such as camera traps nor conventional tracking technologies sufficiently capture the behaviour of individuals. The combination and networking of different sensors in a single system can overcome these limitations, but this potential has been explored only to a limited extent.
2. We present BatRack, a multi-sensor device that combines ultrasonic audio recordings, automatic radio telemetry and video camera recordings in a single modular unit. BatRack facilitates the individual or combined scheduling of sensors and includes a mutual triggering mode. It consists of off-the-shelf hardware and both its hardware blueprints and the required software have been published under an open license to allow scientists and practitioners to replicate the system.
3. We tested the suitability of radio telemetry and audio sensors as camera triggers and evaluated the detection of individuals in video recordings compared to radio telemetry signals. Specifically, BatRack was used to monitor the individual swarming behaviour of six members of a maternity colony of Bechstein's bat. Preliminary anecdotal results indicate that swarming intensity is related to reproductive state and roost switching.
4. BatRack allows researchers to recognize individual bats and monitor their behavioural patterns using an easily deployed and scalable system. BatRack is thus a promising approach to obtaining detailed insights into the behavioural ecology of bats.

2.4.1 Introduction

Many of the important findings and principles of ecology and conservation biology have been derived from behavioural observations (Clutton-Brock and Sheldon 2010), but these are difficult to obtain for small wildlife (Kelly 2008). To further close knowledge gaps, the constraint of ecological surveys between grain and extent must be further resolved. This requires automatic, cost-effective and data-efficient (i.e. triggered) observation systems that provide comprehensive sensor combinations and enable automatic observation at the individual level.

Video recordings are often used to observe the behaviour of individuals (Caravaggi et al. 2017), but for small species camera traps are effective only over short distances (Randler and Kalb 2018). The observation of bats is particularly difficult due to their nocturnal lifestyle in often richly structured habitats. Instead, recordings of echolocation calls are frequently used to monitor the presence/absence of bats (Milchram et al. 2020). These acoustic signals, with their comparatively long range (Enari et al. 2019), can serve as triggers for visual sensors. The combination of audio and video can additionally support the interpretation of the data (Buxton et al. 2018).

However, recognizing individuals on images, particularly small and nocturnal species or species that lack unique visually detectable features, is challenging (Rowcliffe et al. 2008), as is the recognition of individuals based on acoustic recordings (Stowell et al. 2019). By contrast, the automatic tracking of bats using lightweight VHF radio transmitters offers several advantages (Gottwald et al. 2019; Kays et al. 2011; Taylor et al. 2017): (a) VHF signals can be used as triggers for other sensors and (b) they may support the recognition of individuals in video sequences based on comparisons of the VHF signal patterns with the movements observed in the video.

To combine the desirable features of audio and video monitoring, we developed BatRack, a modular observation system that integrates audio, video and automatic VHF radio tracking in a single unit. The three recording technologies can be used separately, simultaneously or in mutual trigger mode, and the corresponding configuration scheduled and switched automatically. BatRack's hardware is assembled from off-the-shelf components and its design and the required software have been published under a GNU GPL 3.0 license.

In the following, we present BatRack's hardware and software, evaluate the suitability of its audio and VHF sensors in triggering the camera, and test the potential of VHF recordings in the identification of individuals in videos, in a case study of the dawn-swarming behaviour (Kunz 1982) of Bechstein's bat *Myotis bechsteinii*. To date, only a few studies have examined this behaviour in detail (Naďo and Kaňuch 2013). Using BatRack's combined sensor approach, we can provide new insights based on individual-related information about the reproductive state and an individual's decision to change roost sites during the night.

2.4.2 Materials and Methods

2.4.2.1 The BatRack system

BatRack combines a core computation component with three sensor units (audio, video and VHF) and tailored analysis modules. Scientists and practitioners can easily assemble, configure and extend the system. Moreover, BatRack is inexpensive (~650€ without a power supply), easily repaired using commodity off-the-shelf (COTS) components (Figure 2.24), and uses free and open source software (FOSS). In addition, it is configurable with respect to the attached sensors as well as their recording ranges, time-based scheduling and mutual trigger mode. A detailed description of the hardware and software modules, including product specifications and blueprints, can be found at the BatRack webpage (https://nature40.github.io/BatRack/).

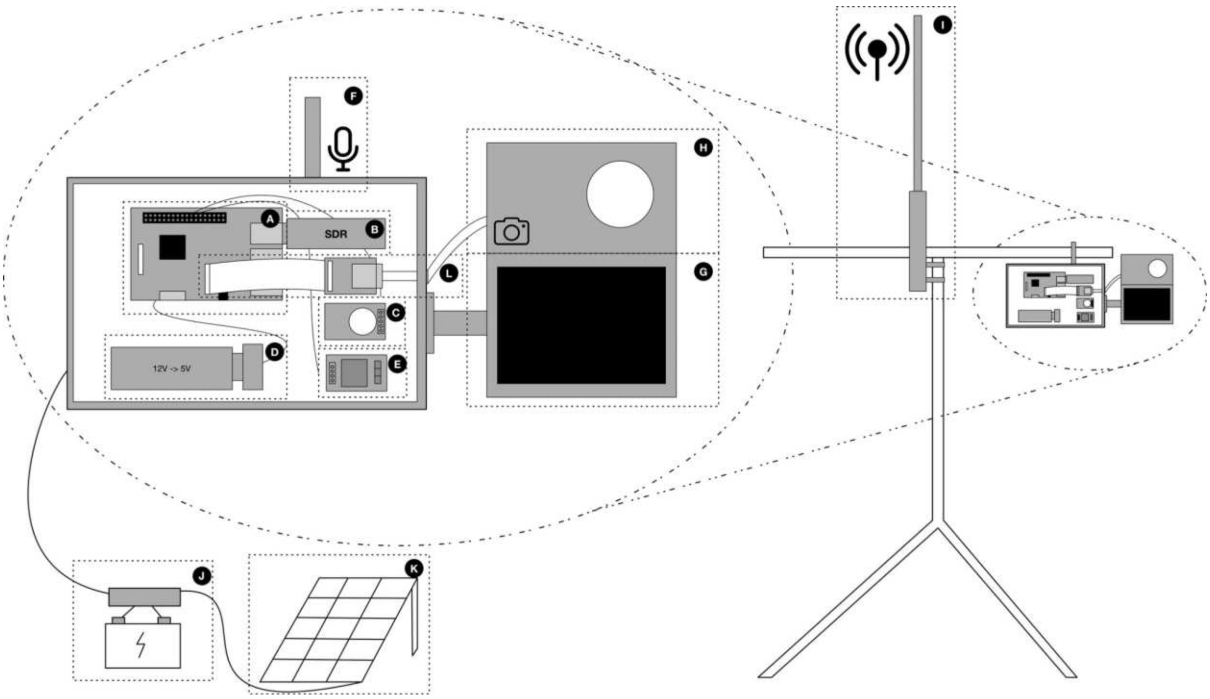

Figure 2.26: Hardware components of BatRack: (a) Raspberry pi mini computer, (b) rtl-sdr dongle, (c) real time clock or LTE stick (d) 12V to 5V converter with USB power supply, (e) KY-019 relay, (f) ultrasonic microphone, (g) IR spotlight, (h) Raspberry pi camera

(NoIR or HQ-camera with removed IR filter), (i) omnidirectional antenna, (j) 12 V battery, (k) solar panel

For easy deployment, the software comes as a customized Raspberry Pi OS image bundle called BatRackOS (https://github.com/Nature40/BatRackOS/releases/), which was built using PIMOD (Höchst, Penning, et al. 2020). The audio module (Figure 2.25a) is implemented using *pyaudio* for audio data retrieval and *numpy* for further audio processing and bat call detection. The sampling rate depends on the hardware (e.g. 384 kHz for Dodotronic Ultramic 384k). The camera analysis module (Figure 2.25b) uses the RPi Camera Web Interface software (https://elinux.org/RPi-Cam-Web-Interface), which allows fast shutter speeds, concurrent camera access and automated exposure settings. Camera recordings are obtained in single image or continuous mode (max 90 frames/s) depending on user-defined settings.

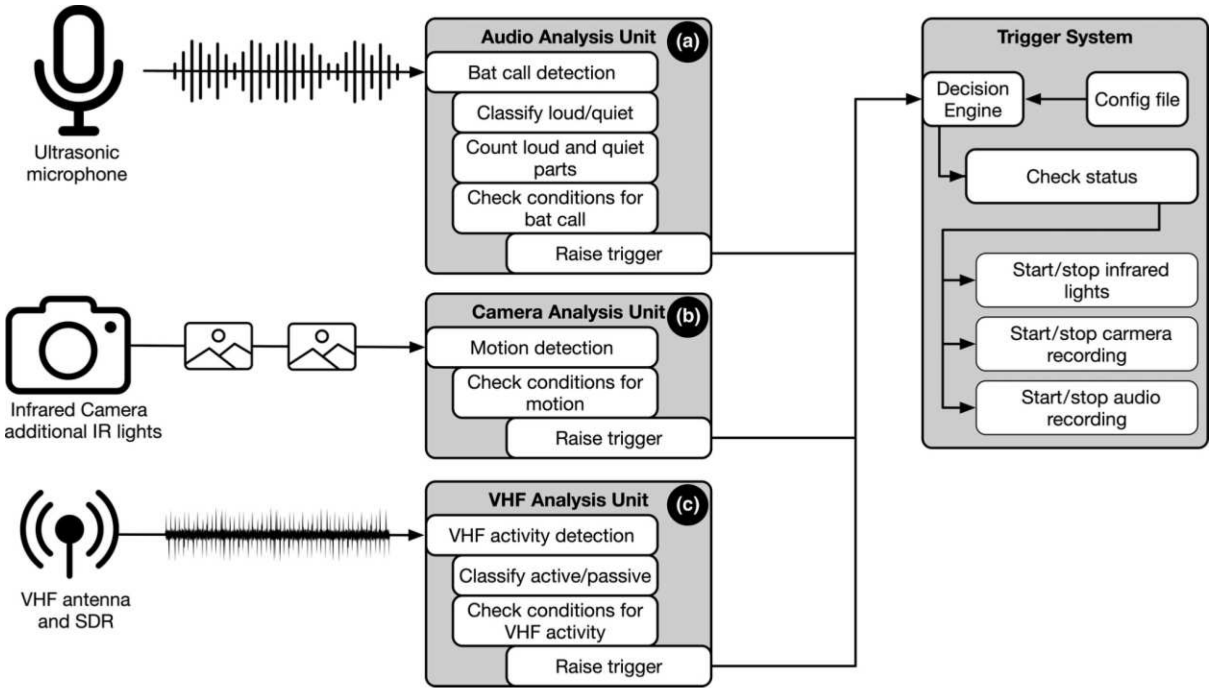

Figure 2.27: Analysis units of BatRack: (a) audio analysis unit (AAU), (b) camera analysis unit (CAU), (c) VHF analysis unit (VAU)

The VHF analysis module (Figure 2.25c) uses the signal detection algorithm described by Gottwald et al., 2019. When a new signal is received, its strength and duration are evaluated such that remote and noisy signals are filtered out. All other signals are classified as active (i.e. flying) or inactive (i.e. resting; (Kays et al. 2011)). A bat is inactive if a standard deviation in signal strength <2 is detected over at least 30 s, and active otherwise (Figure 2.26). If the VHF signals are used to trigger audio or video recordings, only time periods with active signals are written to memory, thus saving storage space and reducing the number of recordings that must be analysed. The operational modes of the analysis modules can be scheduled and configured individually.

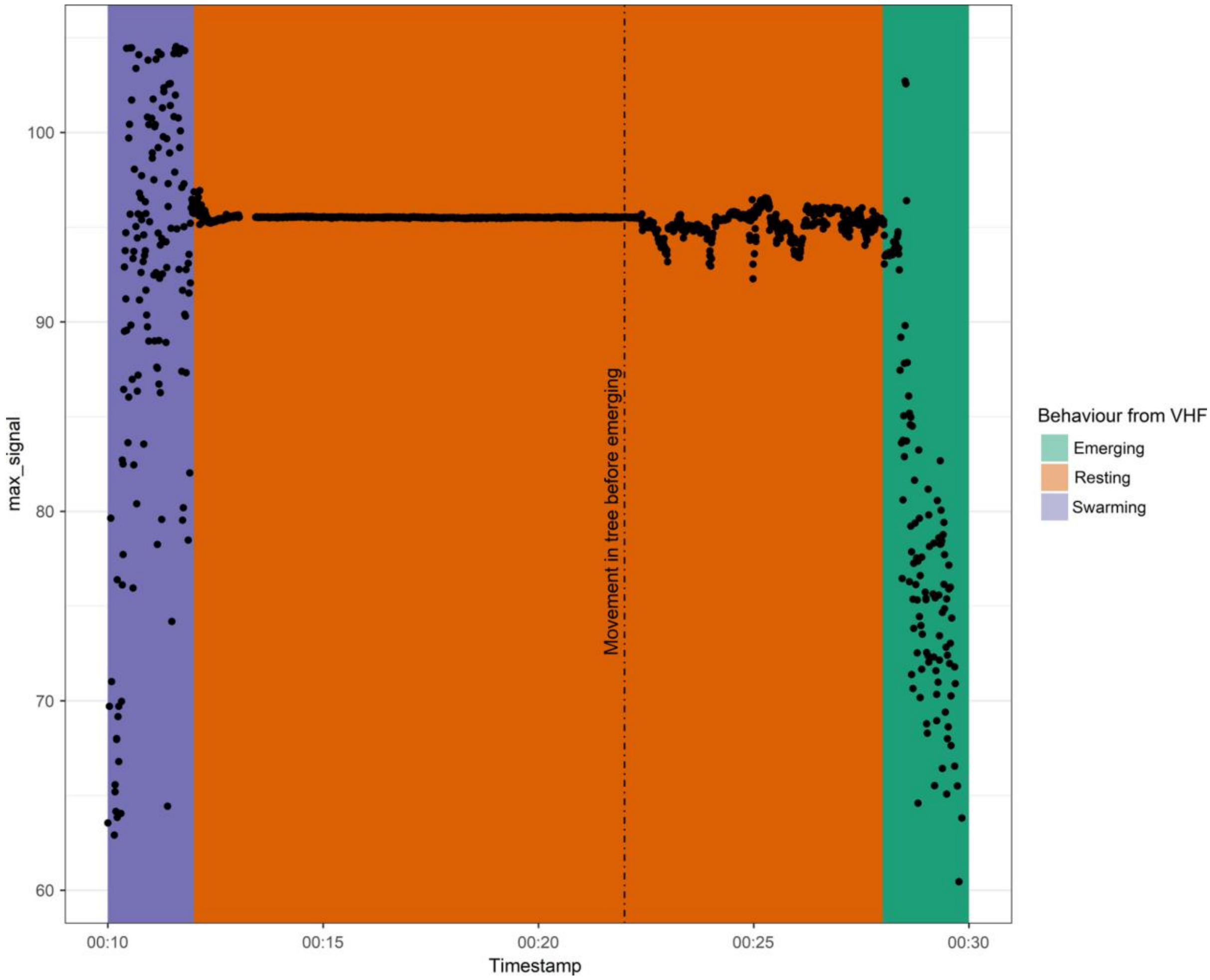

Figure 2.28: VHF signal patterns in relation to the different modes of behaviour. Swarming (purple), passive (orange), emerging from roost (green)

2.4.2.2 Audio-triggered video recordings

The suitability of passive ultrasonic audio observations for triggering video recordings of bats was tested by placing BatRack in front of a known roost of Bechstein's bats *Myotis bechsteinii* for one night. The use of highly sensitive settings (10 dB, 15 kHz) resulted in the triggering of video and audio recordings for 2 s approximately every 10 s. Audio recordings were visualized using BatScope (Obrist and Boesch 2018) and classified as Bechstein's bats, other bats or no bats. Video sequences were manually screened for bats, and the ratio of simultaneous audio and video detections of bats served as the test variable.

To optimize the trigger parameters for the detection of Bechstein's bats, the recorded audio files were post-processed using the trigger algorithm of the audio analysis unit. All possible combinations in the range of 15–50 kHz for the frequency threshold and 15–50 dB for the sound-pressure threshold were tested. All audio recordings classified as Bechstein's bat calls were treated as true positives; all other bat calls were excluded from the training dataset. The maximum F1 score, which is the harmonic mean of precision and recall, was used to select the parameter combination that best minimized false positives while correctly identifying most true positives.

2.4.2.3 VHF-triggered video recordings and individual-related behavioural patterns

To test the suitability of the VHF recordings in camera control and of the VHF signal strength in inferring behaviour, three pairs of Bechstein's bats from the same maternity colony were captured with mist nets between June and July 2020 and fitted with VHF tags. All females, except individual h172498, were in the expected reproductive state at the time of capture (Table 2.3). To monitor the bats, three BatRacks were placed in front of known roosting trees at a distance of 5–15 m for a total of 30 nights between June and August 2020.

Table 2.3: Studied female Bechstein's bat individuals and their pair assignments

ID	**Reproductive state**	**Pair**	**Capture date**	**VHF frequency**
h146480	Pregnant	Pair1	08.06.2020	150.187
h172494	Pregnant	Pair1	08.06.2020	150.128
h172498	Not reproducing	Pair2	23.06.2020	150.172
h146482	Lactating	Pair2	18.06.2020	150.199
h146486	Postlactating	Pair3	15.07.2020	150.199
h146488	Postlactating	Pair3	15.07.2020	150.156

To determine the suitability of VHF receptions in triggering video recordings of tagged individuals, the ratio of expected captures based on VHF patterns to manually screened, actual video captures of at least one visible bat was used as the test variable. To investigate the potential of individual measurements to infer behavioural patterns, in this case swarming and emerging, the VHF data were analysed manually. Swarming was defined as both a signal pattern indicating an active bat and a signal strength above a threshold of −20 dBW for at least 30 s (Figure 2.26, purple). This corresponded to the continuously flying of a tagged individual in close proximity to the sensor unit. Emerging was defined as a resting phase immediately followed by a strong signal, which in turn dropped off very quickly and did not stabilize immediately (Figure 2.26, green).

The observed behaviour of the bats was manually labelled as swarming if the recorded video sequences revealed an individual that moved back and forth in the area of the roost, if the individual briefly approached the tree, or if it left the roost after a short entry. Exits that were not directly followed by re-entry or swarming were classified as emerging.

To determine whether the video-captured bats could be identified as the tagged individuals, the VHF signal patterns and the corresponding movement patterns in the video were compared. Exemplary VHF data and video frames are shown in Figure 2.27. The full video sequence and animated VHF data are provided at the BatRack webpage.

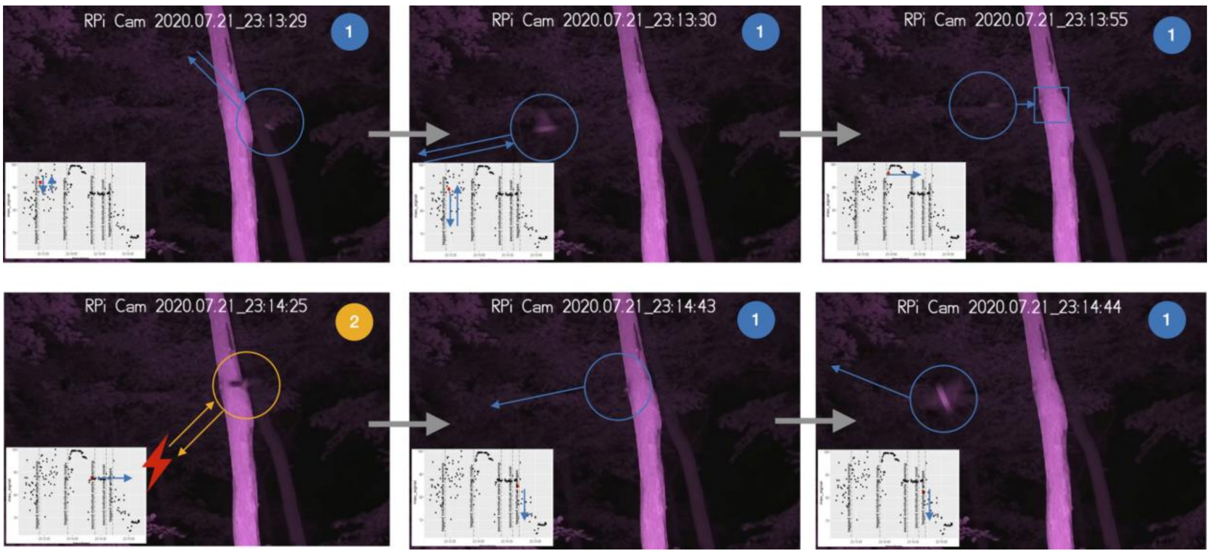

Figure 2.29: Identification of a tagged individual. The VHF signal shows strong fluctuations during swarming (up left and mid). The signal fluctuations decrease significantly after the bat enters the tree (up right, down left). Shortly after a second individual enters the tree (down mid), the tagged bat emerges from the tree (down right)

Unless otherwise stated, all analyses were performed using R (R Core Team, 2020).

2.3.3 Results

2.4.3.1 Audio trigger performance

During the test night, 3,317 audio-triggered audio and video recordings with an average length of 2 s were collected. Bats could be manually identified on 170 video (5.1%) and 663 audio (20%) recordings. From the latter, 272 recordings (41%) most likely originated from Bechstein's bats. For 166 of the 170 (97.6%) videos, a bat call was recorded simultaneously; in 160 cases (94.1%), the call was classified as that of a Bechstein's bat.

After all files with calls that could not be assigned to Bechstein's bats were removed and files without bat calls retained as true negatives, the remaining 2,929 files were processed to determine the optimal trigger parameters. The optimal combination of frequency and volume threshold based on the maximum F1 score (0.91) was 15 dB and 38 kHz. With this combination, 235 out of 274 files containing Bechstein's bat calls (sensitivity = 0.858) were correctly identified; only 5 out of 2,655 negatives were falsely identified as positives (specificity = 0.998).

2.4.3.2 VHF trigger performance

In total, 205 video recordings were captured that matched the VHF sequences classified as swarming or emerging. Of these, 130 (63%) were considered to show swarming and 75 (37%) emerging. Manual screening of the footage revealed one or more bats on 170 of the 205 (83%) sequences. Swarming was successfully detected in 93% of the sequences in which swarming was expected (122 out of 130), and emerging in 65% of the sequences (49 out of 75).

From the 170 (91%) video detections of a bat, in 155 the bat could be identified as the tagged individual with a very high probability, based on comparison of the movement pattern with the VHF signal strength. Among the 49 emerging and 130 swarming events, this was the case for 47 (96%) and 108 (83%), respectively.

2.4.3.3 Individual behaviour patterns

Pregnant and postlactating bats (Figure 2.28; pairs one and three) did not show any apparent differences in their swarming and resting patterns, either between individuals of a pair or between pairs. All four individuals showed a higher swarming frequency on the night of the roost change and on the following night. During the latter, repeated swarming sequences and resting phases at the abandoned tree occurred. The lactating female (Figure 2.28; pair two, h146482), showed a higher frequency of swarming behaviour and resting periods than observed in the non-reproducing female (Figure 2.28; pair 2).

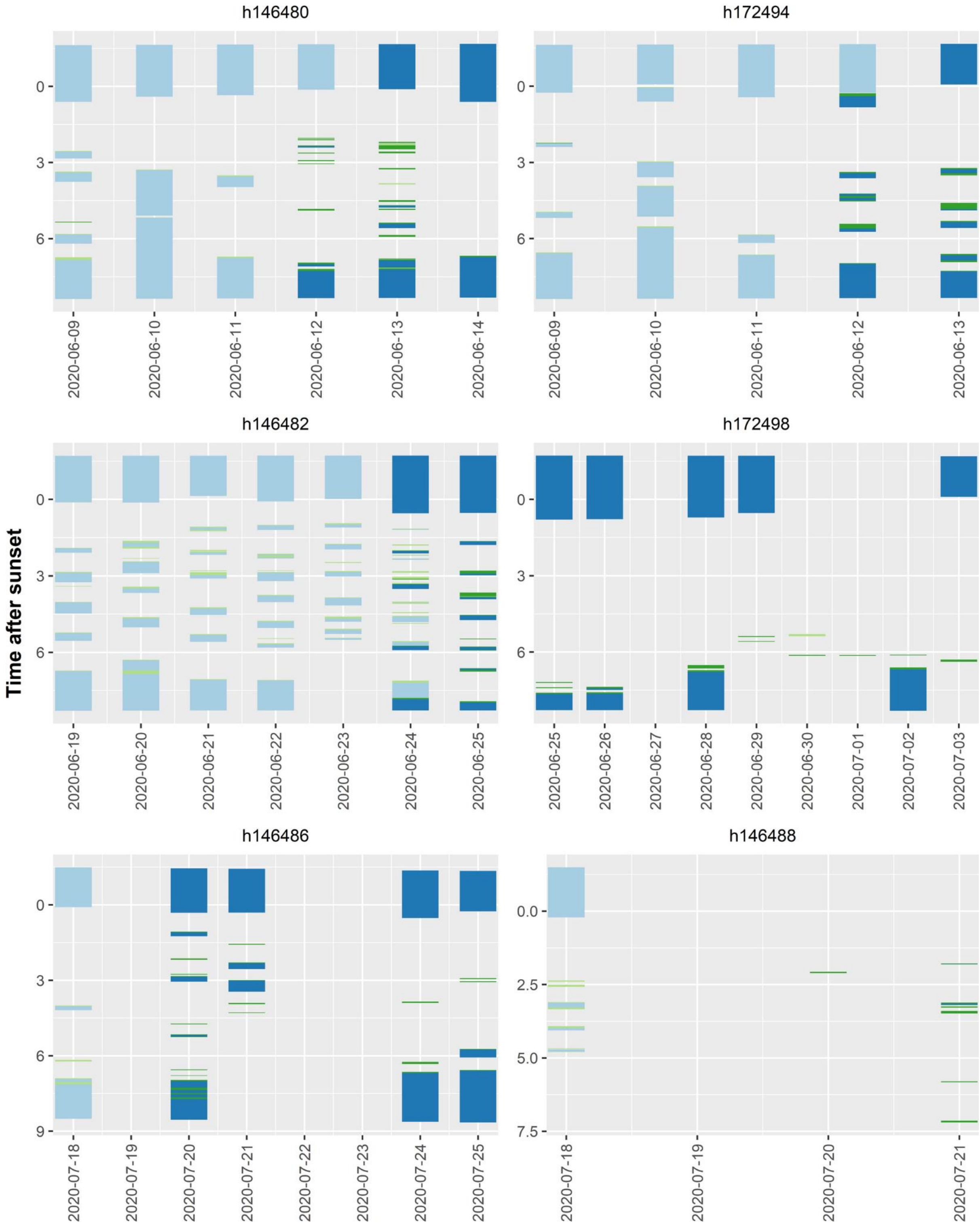

Figure 2.30: VHF-signal-derived behavioural patterns of Bechstein's bat pairs. Blue = inactivity, green = swarming. Gradations in the respective colour scale indicate the roost used for resting (Tree A = lighter blue, Tree B = darker blue) or for swarming (Tree A = lighter green, Tree B = darker green)

2.4.4 Discussion

A prerequisite for understanding dynamic natural environments as socio-ecological systems is data collected using highly automated monitoring systems. Recent developments have shown that the integration of (multiple) sensors and technologies in data acquisition and analysis can provide deep insights into the ecology of different species (Greif and Yovel 2019; Ripperger et al. 2020; Schlägel et al. 2019; Toledo et al. 2020). BatRack offers a highly promising solution in the observation of bats. With its modular COTS design, BatRack can be readily built and easily maintained, allows individual configurations and extensions, and enables both flexible scheduling and the combination of measurements.

BatRack yields reliable occurrence information based on audio or VHF recordings. The latter can be used in the retrieval of basic behavioural information even from a single, nondirectional VHF receiver. Especially for small bat species, the use of either VHF or audio to trigger a video unit results in more energy- and storage-efficient video capture than allowed by purely schedule-based recording. A high detection probability and a substantial reduction in false positives are ensured by applying targeted trigger parameters to the audio unit. Triggering based on the VHF signal results in an even better performance with bats captured almost all the time when one of the tagged bats triggered the recording. In our study, valuable video recordings were obtained even for bats flying up to 15 m away from the sensor.

Our case study on the behaviour patterns of Bechstein's bats illustrates the potential of BatRack. The observations provide first anecdotal indications of an association of increased swarming activity with a change of roost (pair one, three) and weaning of the pup (pair two). However, the advantage of information acquired at the individual level comes at the price of having to tag the animals. Furthermore, the identification of an individual is more difficult if several tagged individuals with similar levels of activity are recorded simultaneously.

The application possibilities of BatRack are manifold. Observations that were previously only possible in the laboratory can be obtained in natural habitats. BatRack is best suited for studies where the observation of bats is linked to a specific and small area (e.g. hibernation roosts, maternity colonies, specific resource occurrences). The focus here is on the study of social behaviour between animals or the use of resources. The mobility of BatRack also makes it possible to complement laboratory studies with field experiments (e.g. changes in resource availability). Moreover, while behavioural contexts can often be inferred from vocalizations, reference recordings are missing for many species (Teixeira, Maron, and Rensburg 2019). This deficiency can be addressed by BatRack, which can be used to collect visual ground truth of the behavioural significance of vocalizations. Thus, BatRack is a promising building block to close knowledge gaps regarding bat behaviour and to develop and evaluate conservation measures.

Acknowledgements

The system was deployed at Marburg Open Forest, the open research and education forest of the University of Marburg, Germany. The research was funded by the Hessen State Ministry for Higher Education, Research and the Arts, Germany, as part of the LOEWE priority project Nature 4.0—Sensing Biodiversity (https://uni-marburg.de/natur40).

Research dimension 2:

Development of data-analysis tools and algorithms

3. Introduction

Given the growing arsenal of automatic sensors, ecology has effectively entered the age of big data but is facing a mismatch between their ever-increasing volume, their complexity, and heterogeneity and the ability of processing and analysing them (Tuia et al. 2022; Thessen 2016; Hampton et al. 2013). High throughput tracking Systems, such as the tRackIT-system, collect huge amounts of data, i.e. several millions of data points per animal to be processed and analysed (Nathan et al. 2022). The BatRack additionally collects video and sound recordings, which, although in theory should only be triggered by events of interest, still contain many false positives.

In order to facilitate the processing of the high amounts of collected data into analysable products, a total of ten different functionalities and tools were developed as part of this thesis. Firstly, algorithms were developed for 1) filtering raw VHF-data collected by the tRackIT-system and the BatRack by frequency, 2) calculating angles and 3) positions, and 4) deriving body temperature from the inter-signal interval of temperature-sensitive transmitters (Chapter 2.2; Gottwald et al. 2019). Secondly, functionalities for the 5) classification of fundamental behaviours from VHF-signal patterns (chapter 3.2; Gottwald et al (in review)), 6) and the detection, and 7) classification of bat calls (Chapter 3.3; (Bellafkir et al. 2022)) are both made available as open source products.

Thirdly, to process the data collected by the tRackIT-system an R-package named tRackIT can be downloaded from GitHub (https://github.com/Nature40/tRackIT). It is specifically tailored to data recorded with one of the sensors from the tRackIT ecosystem (tRackIT-Stations, BatRack), but can also be used for other systems (see tutorials as part of chapter 3.2; Gottwald et al (in review)). Except for the classification of sound data, all described functionalities are included in 8) the tRackIT R package, which also provides 9) a standard data structure to facilitate the exchange of research projects. The same functionalities are also made available as a 10) live service (Chapter 2.4, Höchst and Gottwald et al. 2021), including the visualization via Grafana, enabling real-time monitoring of movement, physical state, and behaviour (Chapter 4.2).

Classifying the activity states of small vertebrates using automated VHF telemetry

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Classifying the activity states of small vertebrates using automated VHF telemetry

Abstract

- The most basic behavioural states of animals can be described as active or passive. However, while high-resolution observations of activity patterns can provide insights into the ecology of animal species, few methods are able to measure the activity of individuals of small taxa in their natural environment. We present a novel approach in which a combination of automatic radio-tracking and machine learning is used to distinguish between active and passive behaviour in small vertebrates fitted with lightweight transmitters (< 0.4 g).

- We used a dataset containing > 3 million signals from very high frequency (VHF) telemetry from two forest-dwelling bat species (*Myotis bechsteinii* (n = 52) and *Nyctalus leisleri* (n = 20)) to train and test a random forest model in assigning either active or passive behaviour to VHF-tagged individuals. The generalisability of the model was demonstrated by recording and classifying the behaviour of tagged birds and by simulating the effect of different activity levels with the help of humans carrying transmitters. The random forest model successfully classified the activity states of bats as well as those of birds and humans, although the latter were not included in model training (F1 0.96–0.98).

- We provide an ecological case-study demonstrating the potential of this automated monitoring tool. We used the trained models to compare differences in the daily activity patterns of two bat species. The analysis showed a pronounced bimodal activity distribution of *N. leisleri* over the course of the night while the night-time activity of *M. bechsteinii* was relatively constant. These results show that even subtle differences in the timing of species' activity can be distinguished using our method.

- Our approach can classify VHF-signal patterns into fundamental behavioural states with high precision and is applicable to different terrestrial and flying vertebrates. To encourage the broader use of our radio-tracking method, we provide the trained random forest models together with an R package that includes all necessary data processing functionalities. In combination with state-of-the-art open-source automated radio-tracking, this toolset can be used by the scientific community to

investigate the activity patterns of small vertebrates with high temporal resolution, even in dense vegetation.

3.2.1. Introduction

The behaviour of an animal can be fundamentally divided into active and passive states (Halle and Stenseth 2000), with the former requiring a much higher energy expenditure (Rowcliffe et al. 2014). Quantifying the distribution of activity periods throughout the day provides important insights into species' responses to their environment, foraging strategies, bioenergetics, and adaptations (Torney, Morales, and Husmeier 2021). Moreover, temporal segregation of species that share the same niche is one recognized mechanism that can facilitate species coexistence (Nakabayashi et al. 2021).

Detailed analysis of individual activity patterns requires high-resolution observations (Nathan et al. 2022), which are often difficult to obtain. The observer's presence may influence animal behaviour and thus bias conclusions (Crofoot et al. 2010), and continuous observation of elusive or highly mobile species in habitats with dense vegetation is close to impossible (Maffei et al. 2005). Information on medium to large-sized species can be obtained using camera traps, GPS transmitters, and accelerometers (Kays et al. 2015), as demonstrated by investigations of dynamic habitat and resource use (Wyckoff et al. 2018), behaviour (Freeman et al. 2010), and migration and dispersal (Walton et al. 2018). However, these devices are of limited use for small animals (<100 g), due to low detection probabilities, the trade-off between transmitter size and weight, battery life, and data-collection intensity (Wikelski et al. 2007; Hallworth and Marra 2015; Hammond et al. 2016). Newer technical solutions such as the ATLAS system (Nathan et al. 2022) or the Wildlife Biologging Network (WBN) (Ripperger et al. 2020) allow the tracking of small animals with high temporal and spatial resolution, but the required installation effort and costs remain high.

Very high frequency (VHF) telemetry has been employed in wildlife tracking since the 1960s (Cochran et al. 1965), with the ongoing miniaturisation of VHF transmitters (< 0.2 g) allowing the tracking of small taxa (body mass < 5 g), ranging from large insects to small vertebrates (Naef-Daenzer et al. 2005). Some studies take advantage of the fact that even small movements of tagged animals result in discernible variations in the strength of the received signal (Kjos and Cochran 1970) that reflect changes in the angle and distance between the transmitter and receiver (Figure 3.1). However, collecting reasonable amounts of data on activity bouts using manual radio-telemetry requires an enormous amount of fieldwork, which implies a high level of wildlife disturbance (Kenward 2000), and the risk of missing critical events in the life of the tagged individuals is high (Lambert et al.

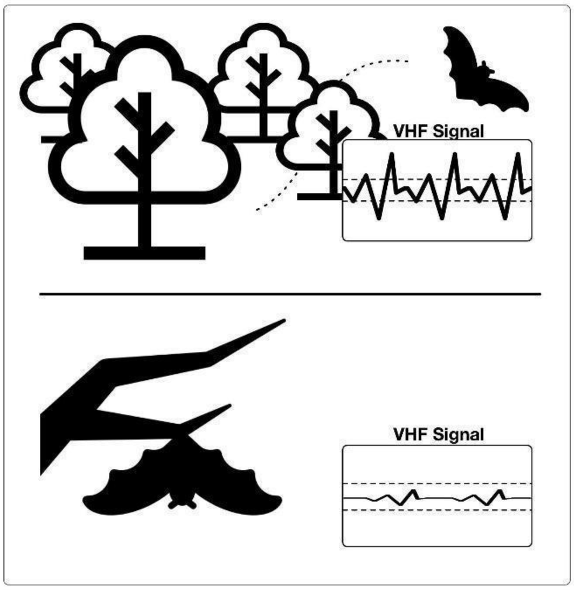


Figure 3.1: Principle of activity-recognition-based very high frequency (VHF) signal patterns. Top: flying bat; bottom: resting bat. The amplitude and variation of the signal strength over time increase when the tagged individual is moving

2009).

Kays et al. (2011) proposed a method for automatically classifying active and passive behaviour based on a threshold in the difference in the signal strength of successive VHF signals recorded by a customised automatic radio-tracking system. However, this system could only track one tag at a time, resulting in a low temporal resolution (i.e., a few seconds of observations every 10 min due to switching through frequency channels). High-throughput tracking systems (<10-s data interval, many individuals at a time) are now widely available and enable ground-breaking research in animal behaviour, evolution, and ecology (Nathan et al. 2022). In recent years, with the ongoing development of low-cost open-source solutions, automatic VHF radio-tracking now enables such high resolution capacities. These systems allow the tracking of many individuals simultaneously and with a very high temporal resolution (seconds) over the complete tagging period (Taylor et al. 2017; Höchst and Gottwald et al. 2021). Continuous, high-resolution recording of the VHF signals makes the entire signal pattern available for subsequent data analysis.

In this work, we build on the methodology of Kays et al. (2011) by calibrating an ML method, i.e., a random forest model, based on millions of data points representing the behaviours of multiple tagged individuals of two temperate bat species (*Myotis bechsteinii*, *Nyctalus leisleri*). Machine learning (ML) algorithms are optimised for the recognition of complex patterns in a dataset and are typically robust against factors that influence signal propagation, such as changes in temperature and humidity, physical contact with conspecifics and/or multipath signal propagation (Alade 2013). ML approaches may provide substantial improvements in the accuracy of individual activity states compared to threshold-based approaches.

Although deep learning methods have been successfully applied to several ecological problems where large amounts of data are available (Christin, Hervet, and Lecomte 2019), we chose a random forest model due to the following reasons: (a) developing a (supervised) deep learning method requires considerable effort for selecting an appropriate neural network architecture, choosing an appropriate framework to implement the neural network, training, validating, testing, and refining the neural network (Christin, Hervet, and Lecomte 2019), (b) our classification tasks resolve to a simple binary classification of active/passive states based on tabular data. In this setting, tree ensemble methods such as random forests seem to have clear advantages - they are less computationally intensive, easy to implement, robust, and at least as performant as deep learning (Shwartz-Ziv and Armon 2022), and (c) in a large study comparing 179 classifiers applied to the 121 classification data sets of the UCI repository, random forests are the best classifiers in over 90% of the cases (Fernández-Delgado et al. 2014).

Our random forest model was used in conjunction with recent developments in automated radio-telemetry (Gottwald et al. 2019; Höchst and Gottwald et al. 2021) to develop a toolset that allows researchers to record the activity patterns of even very small species (body mass < 5 g) in their natural habitat and with high resolution. The method was tested by applying it to independent data from bats, humans, and a bird species and then comparing the results with those obtained using the threshold-based approach of Kays et al. (2011).

In our method, activity states are recognised with high temporal resolution (< 10 s) and high accuracy. In the following, we provide detailed information on the application of the random forest model and its validation using data on the behaviour of tagged bat and bird individuals generated with an open-source multi-sensor tool (Gottwald and Lampe et al. 2021). In a case study, we demonstrate the use of the approach to detect differences in activity patterns between those of the two forest dwelling bat species *Myotis bechsteinii* and *Nyctalus leisleri*. Detailed information on data processing and analysis is provided, along with an R package, example scripts and data, all stored in an open data repository.

In the next sections we detail our process for developing and validating a random forest model to classify VHF signals based on activity data gathered on bats, birds and humans. We then showcase the possible insights in wildlife monitoring that our approach may bring by providing an ecological case study focusing on the comparison of activity patterns between two bat species. All data, trained models, analysis scripts and tutorials are made available within the tRack-IT R package in a hope to promote broad application in wildlife monitoring and ecology.

3.2.2 Field methods

3.2.2.1 Study area

The study was conducted in the Marburg open Forest (MOF), Hesse, Germany, a densely vegetated mixed forest of 200 ha, dominated by European beech (*Fagus sylvatica*) with some clearings and a relatively strong relief for low mountain ranges (lowest elevation ~ 200m, highest ~ 400m) (Figure 3.2). The forest is home to 13 species of bats and 43 species of birds.

3.2.2.2 Tagging of bats and birds

Every year, we caught and then tagged bats and birds with customised VHF-transmitters of different sizes and weights (V3+, Dessau Telemetrie-Service; 0.3 g 1 g). Tag weights were always <4% of the body mass of the tagged individual (see S2 for technical details, methods and permits). For the ecological case study on bats, we captured and tagged 91 bat individuals from two focus species (66 *M. bechsteinii* and 25 *N. leisleri*). For the evaluation of our approach (see “transferability to small diurnal flying vertebrates” section) we used data of 19 bird individuals tagged in another study conducted in parallel (1 *Leiopicus medius,* 3 *Cyanistes caeruleus,* 3 *Erithacus rubecula,* 3 *Garrulus glandarius,* 3 *Parus major,* 3 *Sylvia atricapilla,* 3 *Turdus merula).* The frequency separation between transmitters used simultaneously was at least 3 kHz.

3.2.2.3 Radio-tracking

From 2018 to 2021, we operated a network of 15 custom-designed automatic radio-tracking stations (henceforth 'tRackIT-stations'; (Höchst and Gottwald et al. 2021; Gottwald et al. 2019)) distributed over the MOF (Figure 3.2). The stations recorded signal frequency, duration, and strength as well as the timestamp of the signal of all individuals tagged at a given time simultaneously and automatically.

Each tRackIT-station consisted of four directional antennas with moderate directivity (HB9CV-antenna). While this antenna design reduces the reception range to <1000m in hilly and vegetated terrain, it guarantees overlapping radiation patterns of neighbouring antennas which was necessary for bearing calculation and subsequent triangulation as described in Gottwald et al. (2019). However, tracking of positions of tagged individuals is not part of this study. The towers of the stations had a height of approximately 8m and antennas were oriented north, east, south, and west. We permanently monitored a frequency range of 150.000-150.300 MHz.

From 2018 to 2020, we used the paur 4.3 software developed by the open-source project radio-tracking.eu (Gottwald et al. 2019) but switched to the tRackIT- operating system (https://github.com/Nature40/tRackIT-OS) in 2021 due to high amounts of noise and frequent software failures that often went unnoticed (Höchst, Gottwald et a. 2021). The tRackIT-system enables live transmission of parameters to assess the health of the stations as well as transmission, processing and visualisation of VHF-signals. The former greatly reduces maintenance time and the latter enables tracking of activity, positions and body temperature in near real time. For a detailed description of the hardware and software, please see Gottwald et al. (2019) and Höchst and Gottwald et al. (2021).

The VHF data was filtered by tag frequency +/- 3 kHz and signal duration +/- 5 milliseconds according to settings given by the manufacturer. For the data recorded with the radio-tracking.eu software, we had to visually assess the success of the filtering procedure and in some cases remove recordings below a station- and frequency-specific threshold in dBW due to high amounts of electromagnetic noise.

In total, we used data from 72 individuals (*M. bechsteinii*: N_{ID} = 52, N_{Obs} = 577,977; *N. leisleri*: N_{ID} =20, N_{Obs} = 204,443) monitored for an average of 19 days (according to battery power) to distinguish active from passive states.

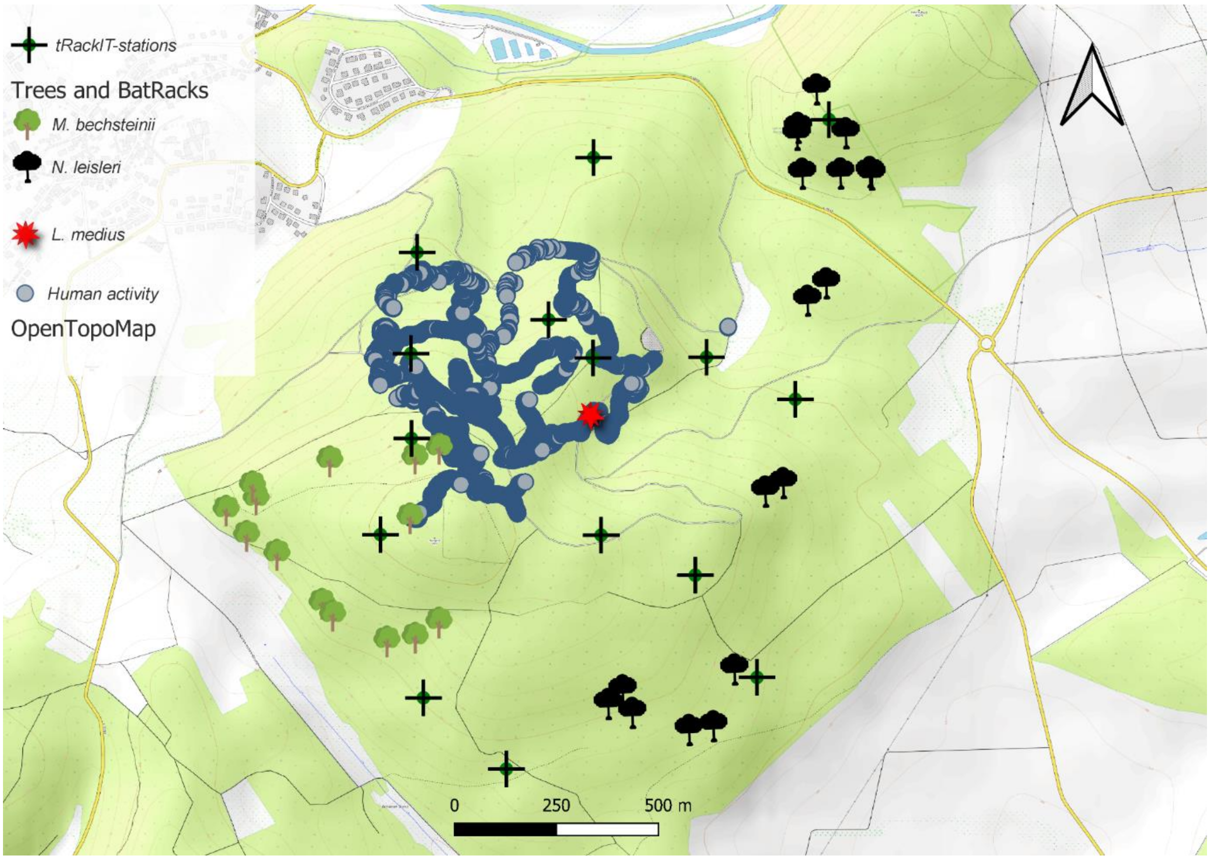


Figure 3.2: The Marburg Open Forest in Hesse, Germany. The map shows the locations of the tRackIT-stations (Gottwald et al., 2019, Höchst and Gottwald et al., 2021), the roost trees of bats (M. bechsteinii, N. leisleri) observed by BatRack multi-sensor stations (Gottwald and Lampe et al., 2021), the breeding site of a woodpecker (Leiopicus medius) and the GPS track (shown in blue) of the activity simulation used to test the transferability of the classification method to birds and humans. (Map data from OpenStreetMap)

3.2.3 A random forest model to classify activity states based on automatically recorded VHF-signals

3.2.3.1 Groundtruth

We used the patterns in the strength of the recorded VHF-signals together with a supervised ML algorithm to classify the activity of the tagged individuals. Supervised ML requires training and test data for implementation. We monitored 23 out of the 72 tagged bat individuals (6 *N. leisleri* and 17 *M. bechsteinii*) using a multi-sensor tool (Gottwald et al. 2021) to supply the random forest model with periods of known activity and inactivity.

First, the roost trees of tagged bats were located via manual radio-telemetry between June 9, 2020 and July 26, 2020 and between May 10, 2021 and August 18, 2021. We then set up custom-made video recorder (‘BatRack') units to automatically record videos of tagged individuals (Gottwald and Lampe et al., 2021; https://nature40.github.io/BatRack/ (vid. 2)). BatRacks consist of a VHF-antenna and an infrared video unit connected to a Raspberry Pi single board computer. We installed the cameras with a focus on the roost entrance and its surrounding area (40-m radius), which allowed the motion of tagged individuals to be captured on the video tracks. The infrared camera unit was automatically triggered by the VHF-signal of the bat transmitters and started recording if the VHF-signal strength exceeded a threshold of -60 dBW, i.e., when a tagged bat flew close to the roosting tree and the BatRack system.

We manually reviewed the video tracks recorded by BatRack units in conjunction with the VHF-signal, and classified the observed behavioural sequence into the categories swarming, passing, entering or emerging from the roost. Sequences that showed swarming, passing or emerging were classified as active, and the time between entering and emerging from the roost as inactive. In addition to the sequences recorded on video, we classified periods of time as active if an individual was recorded in short time intervals on widely separated VHF-receivers (tRackIT-stations and BatRacks). From the three (2020) to nine (2021) BatRacks set in front of a total of 30 roosting trees of 6 *N. leisleri* and 17 *M. bechsteinii* individuals (Figure 3.2), 723 h of behaviour were recorded. For these periods of known activity type, we assigned a passive or active label to the VHF-data recorded by one or more of the 15 tRackIT-stations.

3.2.3.2 Predictor variables

We calculated 29 predictor variables thought to capture the patterns in the signal strengths over time by applying rolling windows of ± 10 data entries, corresponding to an approximate time window of 20 s, to each observation of the classified VHF-data recorded by the tRackIT-stations. We chose the window size to capture the dominant signal strength pattern without smoothing out even short changes of the activity state. To prevent averaging over longer periods, the dataset was split into 5 minute bins per station before applying the rolling windows. For each bin, we selected the receiver with the most data entries, i.e. the best data coverage. We only evaluated bins with at least 60 observations, i.e. three times the window size. This procedure ensures that only stations and receivers with relatively good reception are considered for classification.

To smooth out noise or potentially distracting fluctuations in the signal, we calculated a Hampel filter, in which data points that differ from the window median by more than three standard deviations are replaced by the median(Hampel 1974). We also applied a mean and a max filter on the raw data of the main receiver whereby the respective data point was replaced with the mean or max of the rolling window. Next, we calculated the variance, standard deviation, kurtosis, skewness, and sum of squares for both the raw and the smoothed data, to capture the variability and shape of the data distribution within the window.

Only one antenna is necessary to classify VHF-signals into active vs. passive states. However, agreement between receivers of the same station provides additional information and can improve the reliability of the classification. This is especially likely if the individual is relatively close to the station (< 400 m in our scenario). When data were available from more than one receiver at the same station, we calculated the variance of signal strength between the receiver with the most and the receiver with the second most observations, together with the correlation coefficient and the covariance of signal strength in a rolling window of ±10 data entries. All variables are described in Supplement S1.

3.2.3.3 Training and test data

To give equal weight to each class and to avoid overoptimistic accuracy metrics caused by a comparably well-detected majority class, we balanced the ground truth dataset by randomly down-sampling the activity class with the most data to the amount of data contained by the class with the least data. We then split these balanced data sets into 50% training data and 50% test data for data originating from one receiver. We used the same procedure for data derived from the signals of two receivers, resulting in two training and two test datasets. From a total of 3,243,753 VHF-signals, we assigned 249,796 signals to train the two-receiver model and 588,880 signals to train the one-receiver model (Table 3.1)

Table 3.1: Characteristics of the test and training data obtained from 723 h of video observation on

Setup	Active	Passive	Total	Balanced active (train/test)	Balanced passive (train/test)
1 receiver	588,880	2,654,873	3,243,753	294,440	294,440
2 receivers	249,796	1,469,674	1,719,470	124,898	124,898

3.2.3.4 Model tuning

We used a random forest model as our classification method because it tends to outperform other classifiers, as shown in an extensive comparative study (Fernández-Delgado et al. 2014). This model type is also robust against multicollinearity in predictor variables, especially when used with feature selection procedures (Gregorutti, Michel, and Saint-Pierre 2017), as used in our approach. Since not all variables are equally important to the model and some may even be misleading, we used 50% of the data recorded by either one or two receivers to perform a forward feature selection as implemented in the "CAST" package (Meyer et al. 2018). This resulted in two random forest models, for data collected by one receiver and two receivers, respectively.

3.2.3.5 Groundtruth for controlled walks with human subjects

We conducted a series of 61 controlled walks with a human volunteer to test the reliability of the trained models when applied to various activity patterns and tag positions. This was achieved by moving the VHF transmitters at two different heights, 15 cm above the ground at the ankle and 4 m above the ground, on a pole, around the tRackIT-stations. We simulated inactive states standing still and movements on a small spatial scale were simulated by walking and hopping back and forth over an area of about 1 m^2. We simulated movements at a medium spatial scale by walking within areas of 40 m^2, and multiple back and forth displacements and displacements of at least 200 m were used to simulate large-scale movements. We performed each movement type for 3–10 min at different positions within the north-western part of the study area, which is characterised by a diverse topography and complete forest coverage (Figure 3.2). We recorded the beginning and end times of each sequences and all signals simultaneously recorded by one or more of the 15 tRackIT-stations and then manually assigned the known activity type (active or passive). The human activity dataset consisted of 32,175 data points (26,133 active, 6,042 inactive).

3.2.3.6 Model validation

We applied the trained random forest models to the 50% of the data withheld for testing to evaluate their performance in classifying bat activity. The same trained models were applied to the human activity datasets. In a first step, we calculated the sensitivity (*true positives / (true positives + false negatives)*) and specificity (*true negatives / (true negatives + false positives)*) based on a comparison of the observed data with the activity class attributed by the random forest models for both datasets. Additionally, we calculated the F1 metric as the harmonic mean of the precision (*true positives / (true positives + false positives)*) and sensitivity, the ROC-AUC and the Kappa index, which takes the probability distribution of each class into account. Values vary between 0 and 1 (<0 and <1 for Kappa), with values close to 1 indicating that the model shows an almost perfect agreement (Chinchor 1992; Landis and Koch 1977).

The trained random forest models performed equally well, with F1-scores of at least 0.96 and sensitivities and specificities no less than 0.95, when applied to the validation data of bats and the human activity-simulation (Table 3.2). Whether the tag was positioned 15 cm or 4 m above the ground during the human activity-simulation had no impact on the classification accuracy. The four activity levels simulated by a human were detected similarly well, with sensitivities between 0.95 and 0.97.

3.2.3.7 Comparison to a threshold-based approach

We compared the results of the ML-based approach with those of a threshold-based approach by calculating the difference in the signal strength between successive signals for the test datasets of bats and humans (for methods and results on the bird data see “transferability to small diurnal flying vertebrates” section). We applied a threshold of 2.5 dB, which was deemed appropriate to optimally separate active and passive behaviours in previous studies (Schofield et al. 2018). In addition, we used the optimize-function of the R-package stats (R Core Team, 2021) to identify the value of the signal strength difference that separated the training dataset into active and passive with the highest accuracy (i.e. 1.08 dB) and applied it to the test datasets. We calculated the same metrics as described above, except for ROC-AUC, which requires probabilities for each classification.

Regardless of the method used, all F1 values were < 0.9 (2.5 dB threshold, bats: 0.63, humans: 0.74; 1.08 dB threshold, bats: 0.74, humans: 0.88) and Kappa values < 0.60 (2.5 dB threshold, bats: 0.37, humans: 0.3; 1.08dB threshold, bats: 0.46, humans: 0.53), which correspond to a moderate to fair agreement (Landis and Koch 1977). These values remain well below those obtained from our ML models however.

Table 3.2: Performance metrics of the test datasets classified by the trained random forest model

Dataset	n passive	n active	F1	ROC-AUC	Sensitivity	Specificity	Precision	Kappa
Bats 1 receiver	294172	294172	0.96	0.99	0.96	0.97	0.97	0.93
Bats 2 receivers	110273	110273	0.98	1.0	0.98	0.98	0.98	0.95
Human activity	6150	26504	0.98	1.0	0.97	0.95	0.99	0.90

3.2.4 Ecological case study: comparison of activity patterns in two forest bat species

In the following, we present an ecological case study to highlight the advantages of the fine-scale classification of activity states at a 1-min rate for two species monitored over four consecutive years. Both *M. bechsteinii* and *N. leisleri* are protected species (Habitats Directive 92/43/EEC) endemic to Eurasian forests but they differ substantially in their foraging behaviour. *N. leisleri* feeds on ephemeral insects that occur in large numbers, but only for short periods at dusk and dawn(Rydell, Entwistle, and Racey 1996; Beck 1995) while *M. bechsteinii* partially collects its prey from the vegetation(M. Dietz and Pir 2009) and is thus generally less dependent on the timing of insect flight activity (Rydell, Entwistle, and Racey 1996).

We focused on the following questions: 1) Do *M. bechsteinii* and *N. leisleri* differ in their overall probability of activity? 2) Do *M. bechsteinii* and *N. leisleri* differ in their timing of activity over the course of their circadian rhythms? To answer these questions, we compared the timing of the onset and end of activity periods, the timing of maximum activity and the overall duration of night-time activity bouts using the data processed with the random forest model.

3.2.4.1 Statistical analyses

All analyses were conducted with R v. 4.1.2(R Core Team 2021), using the mgcv package for additive models (Wood 2011).

We used Hierarchical generalised additive models (HGAM) to compare differences in the overnight activity patterns of *M. bechsteinii* and *N. leisleri*. These classes of models can be applied to estimate non-linear relations between responses while allowing for a variety of error terms and random effect specifications (Pedersen et al. 2019; Bogdanović et al. 2021). In this study, we modelled activity over the course of the 24-h cycle as shown in Eq. 1:

$$P(activity)_i = f(time)_i + \zeta_{ID} + \zeta_{DATE} \quad \text{(Eq. 1)}$$

where the probability of activity for observation *i* is modelled as a binomial variable (0: inactive, 1: active) as a function of the time of day (centered around sunset to account for seasonal shifts in daylight). We used a circular cubic spline with 120 equally-spaced knots to constrain the beginning and end of the 24-h cycle so that they matched. Individual identity and date were added as random effects to account for individual, seasonal and yearly effects. Given the volume of data (> 700,000 observations), all models were fitted through the bam() function for faster model estimation.

Given the short timespan between observations, our models had highly autocorrelated residuals ($\boldsymbol{\rho} > 0.50$). While there are no strict guidelines for accounting for autocorrelation with binomial data in HGAMs, the residual autocorrelation was not influenced by the choice of the error family specified (gaussian vs. binomial). We therefore set the autocorrelation manually at a value equal to that of the first lag ($\boldsymbol{\rho}$ = 0.57) using the start_value_rho() from the itsadug package (van Rij et al. 2020). Next, we refitted with the estimated autocorrelation value with an AR1 structure. This procedure successfully accounted for autocorrelation, as evidenced by the decrease in the median autocorrelation to −0.13 in the refitted model. Visual inspection of the autocorrelation confirmed that $\boldsymbol{\rho}$ remained < |0.15| at all lags.

We compared the activity patterns of the two species by contrasting the Akaike information criterion (AIC) values for a model in which species did not vary in their daily activity patterns (Model 0) against one in which the effect of time of day varied between species (Model 1, using the “by = species” argument to specify a time × species interaction). To visualize the fine-scale difference in activity patterns between *M. bechsteinii* and *N. leisleri*, we calculated the difference in spline functions, Δ *f(time)*. This more precisely revealed the period of the day when the two species were most likely to differ in their probability of activity (negative value: $P(\text{activity})_{\text{Bechstein}} < P(\text{activity})_{\text{Leisler}}$, positive value: $P(\text{activity})_{\text{Bechstein}} > P(\text{activity})_{\text{Leisler}}$).

We further characterised the activity patterns of the two bat species by calculating the following metrics based on the predicted values for Model 1:

- Onset and end of activity periods, defined as the first and last time of day when the probability of activity was larger than chance (i.e. p(activity) > 0.5).
- Time of peak activity, calculated as the time of the day when the probability of activity was maximal.
- Activity duration, defined as the duration of the activity period during a 24h period weighted by the average probability of being active (in hours). This metric was calculated as the area under the curve between the onset and end of the activity period.

3.2.4.2 Species comparisons of circadian activity

Nyctalus leisleri and *M. bechsteinii* showed pronounced differences in the shapes of their activity curves and these species differences were also supported by AIC model selection (ΔAIC = 15092, Table 3.3; Figure 3.3). While both species appeared to synchronise their onset of activity with sunset, *N. leisleri* was active an average of 19 min earlier than *M. bechsteinii*. *N. leisleri* also reached peak activity earlier, but its activity markedly declined as soon as *M. bechsteinii* became highly active.

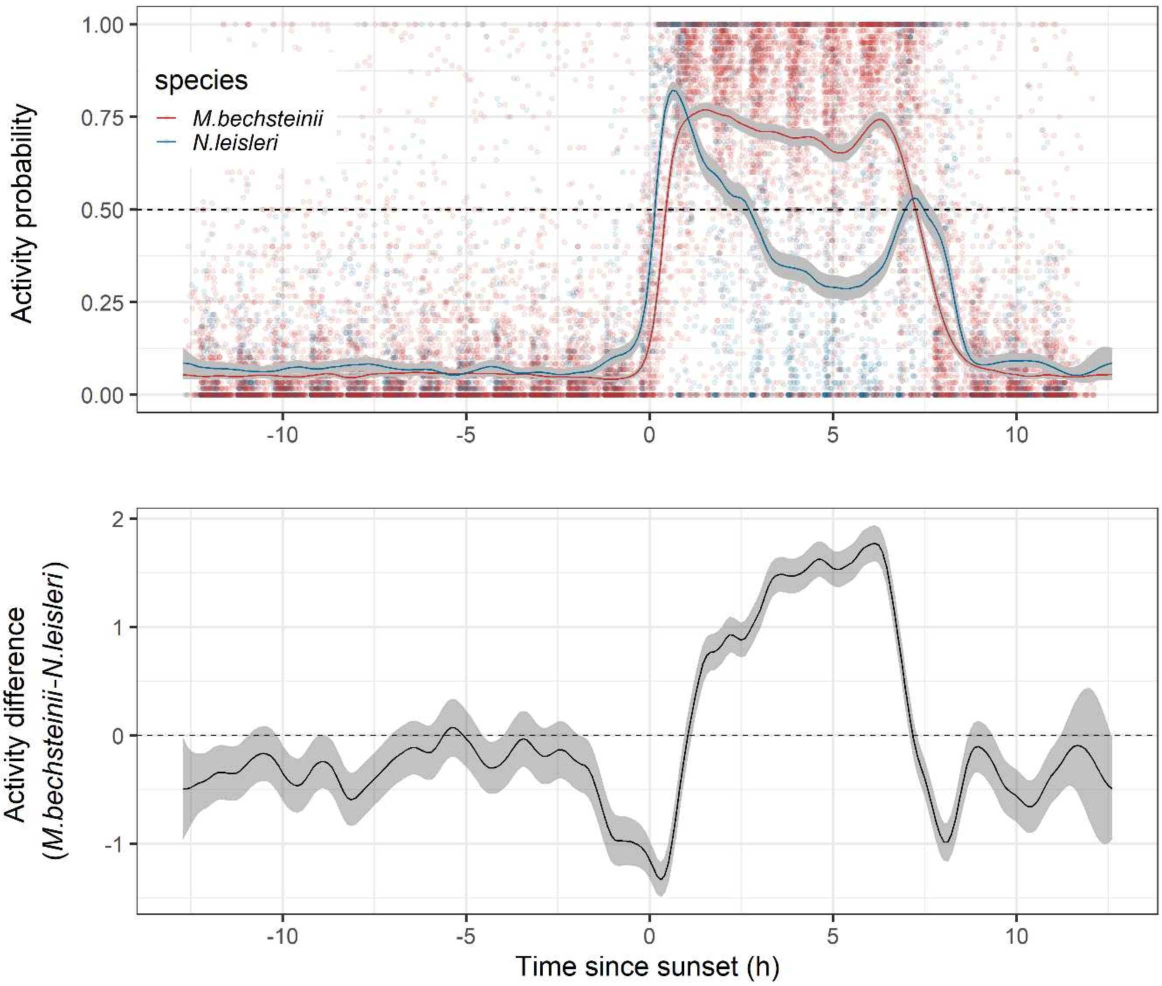


Figure 3.3: Nyctalus leisleri was consistently active sooner than M. bechsteinii, but the latter species had longer periods of continuous activity. Top panel: the points represent the activity probability calculated over 1-h intervals, and the solid lines the predicted values from the best HGAM model. The dashed line indicates the times when the population was equally likely to be detected as active or passive. Bottom panel: difference in the activity probability calculated from the best HGAM model. Positive values indicate a larger activity probability for M. bechsteinii than for N. leisleri.

*Table 3.3: Model coefficients (**β**) and standard errors (SE) and test statistics (z, p) for the linear portion of the additive models (intercept) along with smoothed parameters for nonlinear terms (edf: estimated degrees of freedom, chi-squared and p-values).*

Model 0 (AIC = 263401.1; R^2 = 0.45)						Model 1 (AIC = 248309.1; R^2 = 0.47)					
Linear terms	**ß**	**SE**	**z**	**p**		Linear terms	**ß**	**SE**	**z**	**p**	
Intercept	−1.74	0.13	−12.98	$< 2 \times 10^{16}$		Intercept	−1.74	0.13	−13.29	$< 2 \times 10^{16}$	
Smoothed terms	**edf**	**df**	**X^2**	**p**	**% Variance**	Smoothed terms	**edf**	**df**	**X^2**	**p**	**% Variance**
time	51.84	118	4061287	$< 2 \times 10^{16}$	17.42	time:Leisler	45.82	118	188033	$< 2 \times 10^{16}$	8.83
						time:Bechstein	47.23	118	3571852	$< 2 \times 10^{16}$	22.46
Random effects						Random effects					
ID	67.07	71	1976322	$< 2 \times 10^{16}$	10.18	ID	66.32	71	1824189	$< 2 \times 10^{16}$	4.78
DATE	280.26	306	3084452	$< 2 \times 10^{16}$	17.44	DATE	282.01	306	2421809	$< 2 \times 10^{16}$	10.73

Table 3.4: Activity metrics of N. leisleri and M. bechsteinii. Wake-up and sleep times were calculated as the first and last time when the probability of activity was > 0.5. All times are presented as hours since sunset. The time of peak activity represents the time of day when the probability of activity was maximal. Activity duration was calculated as the area under the curve between wake-up and sleep times.

Metric	*N. leisleri*	*M. bechsteinii*
Activity onset (h)	00:12	00:31
Time of peak activity (h)	00:37	01:33
Activity end (h)	07:23	07:11
Peak P(activity)	0.82 [0.80; 0.84]	0.70 [0.75; 0.79]
Activity density	3.42 [3.23; 3.62]	4.70 [4.56; 4.83]

The latter species was highly active throughout most of the night, as indicated by a significantly higher activity duration (area under the curve when p(activity) > 0.5 [95% CI]; *M. bechsteinii*: 4.70 [4.56; 4.83]; *N. leisleri*: 3.42 [3.23; 3.62]). However, *M. bechsteinii* reached the end of its activity period an average of 12 min sooner than *N. leisleri* (Table 3.4.).

3.2.5 Transferability of the models to diurnal flying vertebrates (birds)

Our previous section shows that the tRackIT-system can provide important insights into ecological differences between bat species with which the model was trained on. We know focus on the broader application of this method to other flying vertebrates.

To test the reliability of the model on birds, we attached a transmitter to the back of a middle spotted woodpecker (*L. medius*), and placed a daylight variant of the BatRack ("BirdRack") in front of its nesting tree for 4 consecutive days. The tree was located on a steep and completely forested slope of a small valley (Figure 3.2). A typical recorded sequence consisted of flying, hopping up the stem, and a very short feeding sequence during which the bird remained motionless at the entrance of its breeding cavity. Since the feeding sequence was usually shorter than three consecutive VHF-signals (~2.5 s), we classified all recorded signals within such a sequence as active. To generate sufficient inactive sequences, 2,200 random data points were sampled from signals recorded by tRackIT-stations each night between 0:00 h and 2:00 h, while the woodpecker was presumably asleep, over four consecutive nights. The dataset of the woodpecker, based on the 75 observed activity sequences, consisted of 17,541 data points (8,741 active, 8,800 inactive).

We applied the two random forest models to all recordings of the tagged woodpecker and calculated the same performance metrics as for bats and human activity for the sequences of known activity. We used the entire woodpecker data set as well as the activity classifications of six additional bird species, each represented by 3 individuals, to assess the transferability of the model to birds of different size and movement habits. Since there are no actual observations for the latter and only partial observations for the woodpecker, we visually compared the classified activity of the woodpecker to patterns expected for diurnal vertebrates. Then, we calculated activity probability in relation to the time after sunset for three individuals from each of six small to medium-sized bird species (Table 3.5) using methods comparable to those of the ecological field study for bats.

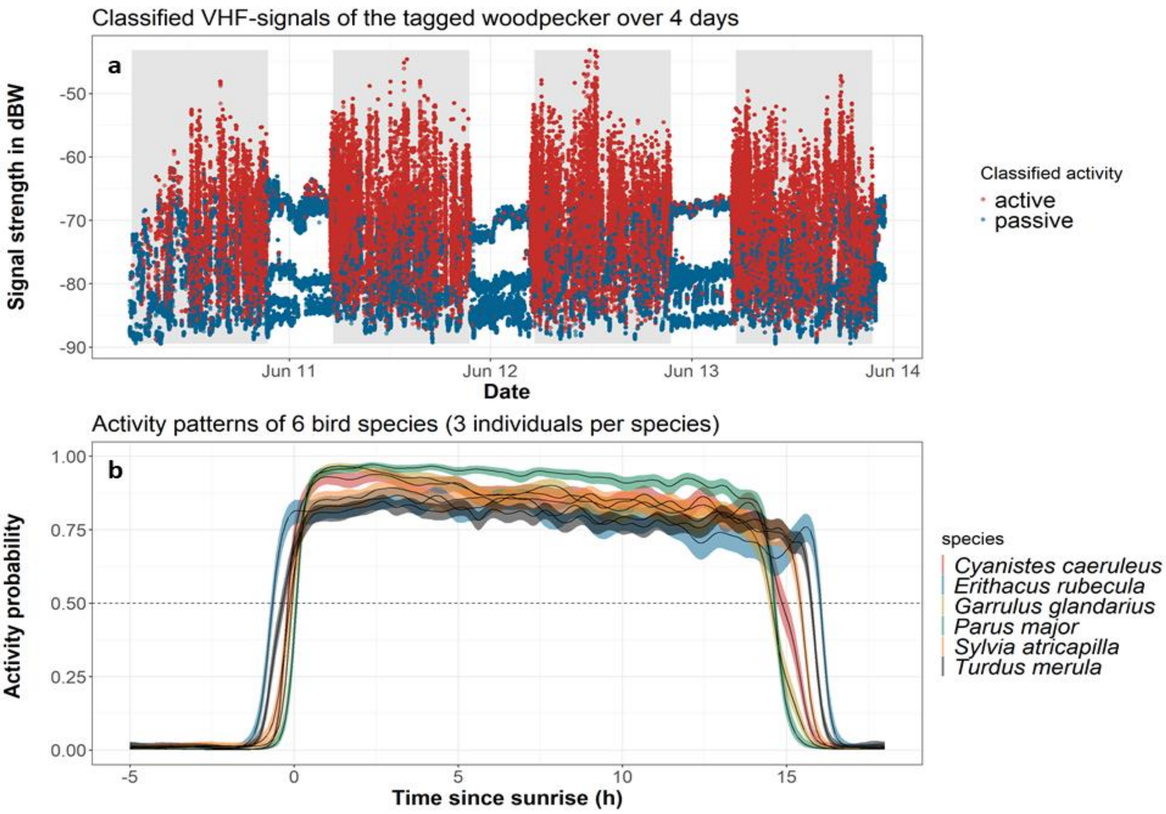
Performance metrics for the sequences of known activity type of the woodpecker were in line with those for bats and human activity (F1 = 0.97; ROC-AUC = 1, Sensitivity = 0.95; Specificity = 1; Precision = 1, Kappa = 0.94). Note that a threshold-based approach also behaved poorly on this dataset (2.5 dB threshold, F1 = 0.62, Kappa = 0.38; 1.08 threshold, F1= 0.79, Kappa = 0.58).

Visual assessment of the active / passive sequences for the woodpecker showed typical patterns of high activity during the day, starting around sunrise (05:12) and ending around sunset (21:30; Figure 3.4). The activity probability in relation to time after sunrise of the six additional bird species also correspond to the expected patterns for diurnal birds (Figure 3.4). Even though no actual observations were available, these patterns suggest a successful classification of the activity of different bird species.

Table 3.5: Number of activity observation (1-Minute resolution) per bird species

Species	Number of observations
Cyanistes caeruleus	55735
Erithacus rubecula	54458
Garrulus glandarius	58088
Parus major	84170
Sylvia atricapilla	59504
Turdus merula	129521

*Figure 3.4: **a)** Signal strength [dBW] from a woodpecker tagged over four consecutive days and nights and the corresponding classification of the bird's activity into active (N = 146,962) and passive states (N = 303, 802). **b)** Probability of activity in relation to time since sunrise of six bird species calculated from activity classifications of three individuals per species (see ecological case study for methods). Periods of high activity are consistent with the diurnal activity patterns expected for these species.*



3.2.6 Data and code availability

To ensure the complete reproducibility of our research, all data and the code used are stored in a data collection at data_UMR, the research data repository of Philipps-Universität Marburg (https://data.uni-marburg.de/; search: “classification of activity states in small vertebrates”). Detailed information on data processing and analysis is provided, along with an R package (https://github.com/Nature40/tRackIT). The trained models are available at: https://doi.org/10.17192/fdr/79. The workflow for model tuning, evaluation and comparison with a threshold-based approach is available at: https://nature40.github.io/tRackIT_activity_classification_model_tuning_and_evaluation/.

Example data processing routines from raw vhf-signals to activity classifications using a small dataset (http://dx.doi.org/10.17192/fdr/104) can be found at the package GitHub page: https://nature40.github.io/tRackIT/.

Reproducible scripts for the ecological case study are available at: https://nature40.github.io/tRackIt_activity_ecological_case_study/ .

R-markdown versions of all scripts can be found in the rmd folder of the tRackIT R-Package.

3.2.7 Discussion

Using a large dataset consisting of the observed behaviour of tagged bat individuals, we trained two random forest models to classify novel data from the same species into fundamental behaviour, and with high precision and high temporal resolution (~1 sec interval). Our approach outperformed previous methods based on a threshold-based approach even when using a value calibrated with a large ground truth dataset. Although not inadequate, the threshold-based approach had generally lower and more variable performance metrics compared to our ML model. We also achieved similar precision when applying the ML models to ground truth data from other species (woodpecker and controlled human walks). The activity probability estimates of 18 additional bird individuals out of six species also matched expected activity patterns for diurnal vertebrates. This strongly suggests that our method generalises well and could be applied to a variety of vertebrates with similar accuracy (e.g. down to a body-mass of 4g with 0.2g transmitter (Naef-Daenzer et al. 2005)).

In the ecological case study, we demonstrate that our approach enables the detection of even subtle differences in the timing of activity according to a species’ ecological preferences (differences in activity onset of < 20 min). Specifically, we were able to show distinct activity patterns for these two species, characterised by a slight shift in their timing of activity and a significantly lower activity of *N.leisleri* during the night. Given that these species have evolved to occupy different ecological niches, these patterns are much more likely due to a synchronisation of activity peaks with prey abundance rather than to an avoidance of competition(Ruczyński et al. 2017). *Nyctalus leisleri*, like other aerial hawking bats, has likely evolved to exploit insect emergence at dusk and dawn, thus avoiding the greater predation risk that may occur at higher light levels (Rydell, Entwistle, and Racey 1996). By contrast, *M. bechsteinii* and other gleaning bats are less constrained to flying insects as a food source such that an onset of activity comparable to that of *N. leisleri* would not bring substantial additional benefit.

Our findings are generally in line with previous observations of the activity patterns of *N. leisleri (Ruczyński et al. 2017; Shiel, Shiel, and Fairley 1999)*. No comparable studies exist for *M. bechsteinii*, but in acoustic studies with results reported at the genus level all-night activity was determined for *Myotis (Perks and Goodenough 2020)*. However, our study is the first to investigate the overlap of these two species within the same study area. Our approach also allows to detect changes in activity probability according to the reproductive status of individuals and indicates that these shifts are species specific (see Supplementary Material S4).

The high precision and high temporal resolution of our approach together with the easy accessibility of the developed methods may open new research avenues on the variations in the activity patterns among and within species in their response to the environment.

A more in-depth analysis of activity bouts as a function of abiotic factors or the detection of changes in patterns indicating, for example, breeding has not been conducted here, but such studies are likely to be feasible. Whether specific behaviours can be recognised (i.e., foraging, parental care, grooming), as is possible with accelerometers, also remains to be determined. The fact that the variance in the signal pattern depends less on the intensity of the movement than on the signal path remains an issue, however. While the amplitude of the measurements from accelerometers can be directly related to different behaviour classes (Kays et al., 2015), the amplitude of stationary recorded VHF-signals also changes due to the distance to the radio tracking station. The spatial context of the receiving stations as well as the localisation algorithms presented in Gottwald et al. 2019 could provide additional information, such as distance to the station and direction of movement. However, for localisations, at least two radio-tracking stations are necessary and the spatial accuracy and reliability of position tracking when operating in cluttered environments such as forests is still under investigation.

The tRackIT-system can currently record up to 90 individuals at a time within the same spatial context, but technology that allows for higher numbers is under development. Given the relatively low costs of the transmitters (~130 €) and tRackIT-stations (~1,500 €), the monitoring of an entire community of small vertebrates at high temporal resolution becomes possible with this system. For instance, a study investigating the activity states of an entire temperate forest bird community is currently conducted in the Marburg Open Forest. The tRackIT-system now allows activity classification in real-time, which opens several exciting research avenues. For example, it is now being used to narrow down the time of death of chicks in meadow-breeding birds to subsequently reduce error bars in nest survival models (https://www.audi-umweltstiftung.de/umweltstiftung/de/projects/greenovation/telemetry-technology.html). Personal observations during the bird-breeding season also showed clear shifts in the frequency and regularity of activity periods during the transition from the non-breeding to the breeding season (J. Gottwald). Future applications may also help automatically determine the (species-specific) onset of the breeding season in songbird communities.

Over the four years of the study, we collected data with two different software designs (radio-tracking.eu and tRackITOS) that show significant differences in data quality. We also covered a range of suboptimal recording conditions caused by topography and vegetation, which leads us to the assumption that the approach presented here is not exclusively applicable to data recorded with tRackIT-stations. Other open-source systems such as Motus (sensorgnome)(Taylor et al. 2017), but also commercial systems such as the Lotek SRX/DX series receivers (Taylor et al. 2017), record comparable data that may be used with the functionalities and models presented here. However, this was not tested as part of this study.

The scientific insights that can be expected from automatic radio-tracking based activity studies have the potential to deepen our understanding of the ecology and behaviour of small animal species in unprecedented ways (Nathan et al. 2022). With the recent advances in open-source automatic radio-tracking (Höchst and Gottwald et al. 2021; Gottwald et al. 2019; Taylor et al. 2017) together with the trained models and data-processing functionalities of the tRackIT R-package, the scientific community is now equipped with an accessible toolset that allows the activity patterns of small animals to be analysed and classified at high temporal resolution.

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Bat Echolocation Call Detection and Species Recognition by Transformers with Self-Attention

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Bat Echolocation Call Detection and Species Recognition by Transformers with Self-attention

Abstract

Biodiversity is important for several ecosystem services that provide the existential basis for human life. The current decline in biodiversity requires a transformation from manual, periodic assessment to automatic real-time biodiversity monitoring. Bats as one of the most widespread species among terrestrial mammals serve as important bioindicators for the health of ecosystems. Typically, bats are monitored by recording and analysing their echolocation calls. In this paper, we present a novel approach for detecting bat echolocation calls and recognizing bat species in audio spectrograms. It is based on a transformer neural network architecture and relies on self-attention. Our experiments show that our approach outperforms state-of-the-art approaches for bat echolocation call detection and species recognition on several publicly available data sets. While our bat echolocation call detection approach achieves a performance of up to 90.2% in terms of average precision, our bat species recognition model obtains up to 88.7% accuracy for 14 bat classes occurring in Germany, some of which are difficult to distinguish even for human experts.

3.3.1 Introduction

Bats (Chiroptera) belong to the most widespread species group among terrestrial mammals. Except for the Arctic, Antarctic, and a few isolated islands, all regions of the earth are inhabited by bats (Kunz 2013). With almost 1,400 recognized taxa, they represent almost one fifth to the mammalian diversity (Frick, Kingston, and Flanders 2020). From pest control to seed dispersal, bats contribute to all four ecosystem services defined in the Millennium Ecosystem Assessment (Kunz et al. 2011). Thus, they are equally important for the ecosystems they inhabit and for mankind whose well-being depends on the integrity of these ecosystems.

Furthermore, bats are important bioindicators for the health of the ecosystems they live in. For example, due to the high trophic level of insectivorous species, fluctuations in bat populations can be indicative of environmental changes affecting their prey of mostly small invertebrates, which are difficult to monitor themselves (G. Jones et al. 2009).

Unfortunately, about one third of all bat species are classified as threatened or data deficient by the International Union for Conservation of Nature (IUCN), and about half of all bat species show a declining or unknown population trend (Frick, Kingston, and Flanders 2020).

To monitor populations of bat species and thus biodiversity at scale, automatic bat echolocation call detection and bat species recognition approaches are required.

With the success of Convolutional Neural Networks (CNNs) in various tasks, audio classification research has evolved over the last decade from models based on hand-crafted features like Mel Frequency Cepstral Coefficients (MFCCs) to CNNs that directly match audio spectrograms to feature representations. Several state-of-the-art bat echolocation call detection and bat species recognition approaches are based on CNN architectures applied to audio spectrograms.

Currently, transformer neural network architectures based on self-attention, such as Vision Transformers (ViT) (Dosovitskiy et al. 2020), are successfully applied in computer vision tasks. While CNNs have an inductive bias, such as spatial locality and translation equivariance, vision transformers have a lower bias and can capture global context even in the first layers of a neural network.

In this paper, we present a novel approach for detecting bat echolocation calls and recognizing bat species in audio spectrograms. It is based on a transformer neural network architecture and relies on self-attention. To the best of our knowledge, this is the first work that utilizes fully attentional architectures to solve the problems of bat echolocation call detection and bat species recognition.

In particular, our contributions are as follows:

- We present a novel self-attention approach for bat echolocation call detection and bat species recognition in audio spectrograms. It is based on pre-trained data-efficient image transformer models used as components in a workflow that we developed to process audio spectrograms of recorded bat echolocation calls.
- We show that the presented approach outperforms other state-of-the-art approaches for bat echolocation call detection and bat species recognition on several publicly available data sets. Our approach for bat echolocation call detection achieves a performance of up to 90.2% in terms of average precision, and our bat species recognition model obtains up to 88.7% accuracy for 14 bat classes occurring in Germany, some of which are difficult to distinguish even for

human experts. Furthermore, we demonstrate that the distribution of the training and test set is an important factor for determining the recognition accuracy.

- We make our transformer models for bat echolocation call detection and bat species recognition publicly available at https://github.com/umr-ds/transformer4bats. In this way, other researchers can use our models to detect and recognize bat calls contained in their audio recordings.

The remainder of the paper is organized as follows. Section 2 discusses related work. The proposed approaches for bat call detection and recognition are presented in Sect. 3. Our experimental results are described in Sect. 4. Finally, Sect. 5 concludes the paper and outlines areas for future work.

3.3.2 Related Work

Since manually detecting and recognizing bat echolocation calls is a tedious and time-consuming task, several automated methods have been proposed in the literature. For many years, handcrafted features extracted from the length of the call, the frequencies, and amplitudes were used to train machine learning algorithms. In recent years, several approaches based on CNNs outperformed these methods by learning the features in an end-to-end manner. Usually, the audio recordings are transformed into spectrograms that are then processed by a CNN.

Bat populations are found across all continents except the Arctic, the Antarctic, and a few isolated islands. Nevertheless, each region has an individual set of bat species. Roemer et al. attempted to build a universal model to classify bat calls into species around the world (Roemer, Julien, and Bas 2021). To do so, they first classified the calls into sonotypes and refined the results by determining the exact species. They used random forests to realize their approach. Current approaches often use CNNs and mostly consider a specific geographic region. Consequently, models are available for regions in Europe (Paumen et al. 2021; Schwab et al. 2022), North America (Tabak et al. 2021), the Middle East (Zualkernan et al. 2020), and Asia (X. Chen et al. 2020; Kobayashi et al. 2021).

While most approaches are based on spectrograms generated from standard waveform audio recordings, Tabak et al. (Tabak et al. 2021) trained their CNN on sparse zero-cross data. Using a small ResNet-18 (He et al. 2016) neural network architecture, they achieved good results on out-of-distribution data. The way spectrograms are generated plays an important role for the given task. Zualkernan et al. (2020) compared three different kinds of spectrograms, namely Short-Time Fourier Transform (STFT), Mel-Scaled Filterbanks (MSFB), and Mel-Frequency Cerpstral Coefficients (MFCC). For their use case, they found that Mel-Scaled Filterbanks work best. Paumen et al. (2021) decided to work with MFCCs for data efficiency reasons. Most approaches make use of the Short-Time Fourier Transform (X. Chen et al. 2020; Kobayashi et al. 2021; Schwab et al. 2022).

Zualkernan et al. (2020) and Paumen et al. (2021) considered 3 and 1 second snippets, respectively, extracted from spectrograms, whereas the majority of approaches extract single calls (X. Chen et al. 2020; Kobayashi et al. 2021; Schwab et al. 2022) and can thus make use of a higher input resolution per call. Chen et al. (2020) showed how manual labeling of bat call events can be improved by a simple peak detection algorithm for detecting potential regions, in order to significantly speed up the labeling process by human experts (Kobayashi et al. 2021; Schwab et al. 2022).

Nevertheless, the human labeling process is a sophisticated task, infeasible for larger data sets, and the results can differ significantly between different annotators, resulting in a low inter-coder reliability (Mac Aodha et al. 2018). Furthermore, an extensive publicly available bat call data collection is missing. In particular, certain species are inadequately represented in the existing data sets. To deal with small data sets and the class imbalance problem, Kobayashi et al. (2021) used data augmentation. The authors applied Cutout, Random Erasing, and Salt-and-Pepper noise to the spectrograms.

In terms of the considered bat species, Schwab et al. (2022) are closest to our work. The authors first applied a band-pass filter to the audio signal and computed the corresponding spectrogram. Next, they detected peaks in that spectrogram and cut out 10 ms windows around these points. A first CNN was trained to distinguish bat calls from noise and background. Based on the results of this model, a second CNN determined the exact bat species. Optionally, both models can be integrated into a single neural network to make the process more lightweight. The best results were achieved using a modified ResNet-50 (He et al. 2016) architecture. Paumen et al. (2021) considered German bat species too, but merged similar bat species into higher classes.

While most papers work with species that partly stem from the same kind, Zualkernan et al. (2020) took solely groups of bat species into account, which is a much simpler task. In our approach, bat species are only merged if they are not distinguishable by human experts. A list of the bat species we considered is presented in Table 3.6. To tackle the problem of hard to classify weak signals, Chen et al. (2020) introduced a weak label along with a rechecking strategy that verifies whether the neighboring regions of the weak call belong to the same class. This is a helpful strategy for noisy, passively recorded data. However, this strategy requires additional manual labeling effort.

Due to the different species being considered and the lack of publicly available data sets, it is difficult to compare the existing approaches on bat call recognition using deep learning techniques. Furthermore, classes with few samples can often be found in the data sets, which has the risk of overfitting. To classify bat calls, these calls need to be detected in audio recordings in the first place. This corresponds to localizing audio events in time. Similar to recognition, detection has been performed using handcrafted methods such as amplitude threshold filtering or detection of changes in frequency. However, most available algorithms are closed commercial projects and thus lack transparency.

Contrary to that trend, Mac Aodha et al. (2018) developed an open-source software based on CNNs. Their software called BatDetective is based on a sliding window approach over time-expanded and band-pass filtered FFT spectrograms. Since the used data sets contain rather noisy audio recordings, the mean amplitude of each frequency band is removed (Aide et al. 2013) as a denoising operation. The resulting image is then fed into a CNN using a sliding window approach, where the window size is 23 ms. The final probabilities of the binary classification problem are obtained by applying non-maximum suppression. BatDetective achieves the best quantifiable results among all available tools by a large margin.

In recent years, CNNs have been the best choice for detecting and recognizing bat calls. Meanwhile, in many computer vision tasks, CNNs have been outperformed by transformer architectures. Transformers are based on self-attention mechanisms and have been applied, e.g., to image classification (Dosovitskiy et al. 2020; Touvron et al. 2021), audio event tagging (Gong, Chung, and Glass 2021), and image captioning tasks (Cornia et al. 2020; Yu et al. 2020).

3.3.3 Methods

Self-attention architectures, in particular transformers, have recently become the model of choice in natural language processing (NLP), where they are often pretrained on a large corpus of text and fine-tuned for different downstream tasks. Furthermore, transformer architectures, such as Vision Transformers (ViT) (Dosovitskiy et al. 2020), have also become state-of-the-art approaches in several computer vision tasks.

In an attempt to explain this success, Cordonnier et al. (2019) showed that self-attention can express a CNN layer and that convolutional filters are learned in practice by self-attention (Cordonnier, Loukas, and Jaggi 2019). Furthermore, Dosovitskiy et al. (2020) concluded that transformers do not generalize well when trained on insufficient amounts of data. Contrary to this claim, Touvron et al. (2021) showed that it is possible to learn a model that generalizes well using only the ImageNet-1k data set at training time. The authors presented a training process and a distillation procedure based on a distillation token, which plays the same role as the class token used by Dosovitskiy et al. (2020), with the exception that it aims to reproduce the distribution of the label vector estimated by the teacher. The authors showed that the trained fully attentional model (i.e., DeiT) can achieve competitive state-of-the-art results on ImageNet.

This approach was also successfully used in the Audio Spectrogram Transformer (AST) (Gong, Chung, and Glass 2021) for audio event tagging using audio set[13] (Gemmeke et al. 2017). In the following, we present a novel self-attention approach based on pre-trained DeiT models for the automated analysis of bat calls in audio recordings. In Section 3.3.3.1, we describe our detection approach for bat echolocation calls, whereas our recognition method is explained in Section 3.3.3.2.

3.3.3.1 Bat Echolocation Call Detection

Our detection approach is based on self-attention and hence free of any convolutional layers. In the following, we describe the steps of our detection workflow, as shown in Figure 3.5. First, we generate a spectrogram from the audio recordings to enable the use of pre-trained image transformer architectures. Instead of using traditional MFCCs or PLP (perceptual linear prediction) coefficients, we use log Mel filterbank features that are state-of-the-art for bat call detection and recognition (Zualkernan et al. 2020).

The input audio waveform of t seconds, time-expanded (TE) by factor 10, is converted into a sequence of 128-dimensional log Mel filterbank features computed by applying a 23 ms TE Hanning window with a large overlap of 84% to better capture short calls.The resulting spectrogram is then split into multiple views with a sliding window approach, where each view is a 128 × 64 spectrogram that is equivalent to 230 ms TE. We selected the window size to be sufficiently long to capture the longest search calls in our training data. Each such view is then split into 16 × 16 patches with a stride of 10 and fed into a linear projection operation before using them as the input sequence to the transformer model to verify the presence of a bat call.

[13] https://research.google.com/audioset/

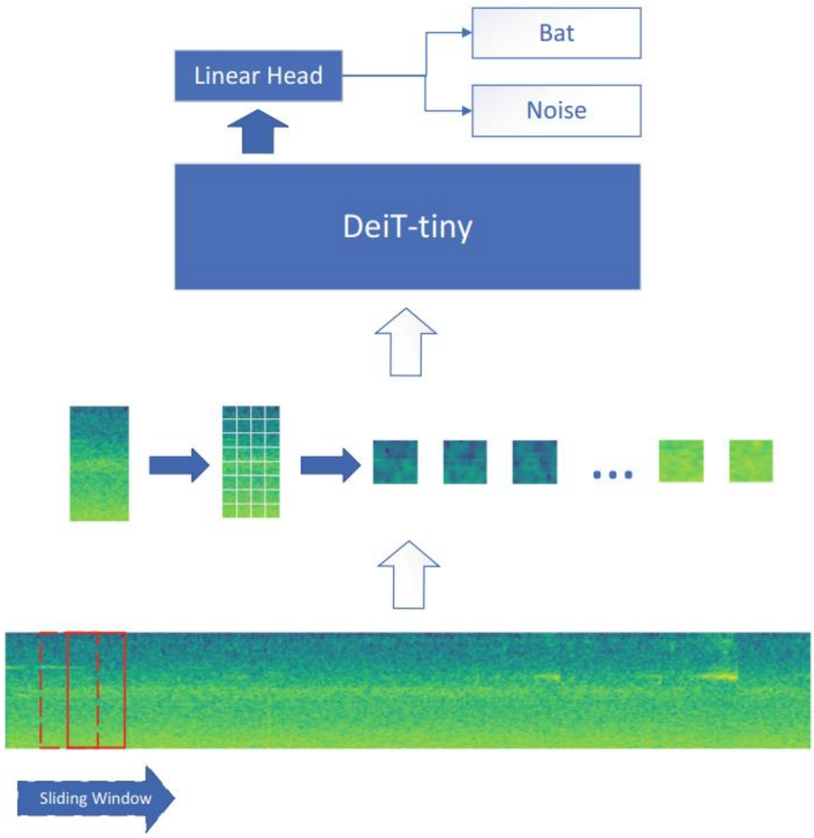

Figure 3.5: Workflow for bat echolocation call detection

The model takes (H − 16)/10×(W − 16)/10 patches, which is 60 for an input of 128 × 64. We use overlapping patches that were shown to be beneficial by Gong et al. (2021). Since we split the original spectrogram into overlapping views, a one-dimensional non-maximum suppression operation is required to determine the final predicted time positions.

Our transformer architecture is a pre-trained tiny vision transformer (i.e., DeiT-tiny) (Touvron et al. 2021) with approximately 5 million parameters. This architecture consists of 12 layers, each layer having 3 self-attention heads. The transfer learning approach with respect to processing audio data is applicable since the vision transformer can handle arbitrary sequence lengths. However, the pre-trained position embeddings need to be modified, since DeiT-tiny is pre-trained with a resolution of 224, which results in 14 × 14 position embeddings with patch sizes of 16 × 16. Since using randomly initialized position embeddings leads to poor overall performance in our experiments, we adopted the approach used by Gong et al. (2021) and cut the first and second dimension of the 14 × 14 positional embedding to 12 × 5 and use it as the positional embedding in our training phase. Furthermore, we replaced the classification layer of the DeiT-tiny model to adapt the architecture to our audio detection task and initialized it randomly.

3.3.3.2 Bat Species Recognition

To build our recognition model, we consider only German bat species of the Tierstimmenarchiv[14] data set. Some of the bat species have very similar echolocation calls, e.g., the species of the Myotis kind. Nevertheless, we do not merge any of the classes, but try to distinguish them as annotated except for the Whiskered bat and the Brandt's bat which are not distinguishable by their echolocation calls. All species considered for training our model are presented in Table 3.6.

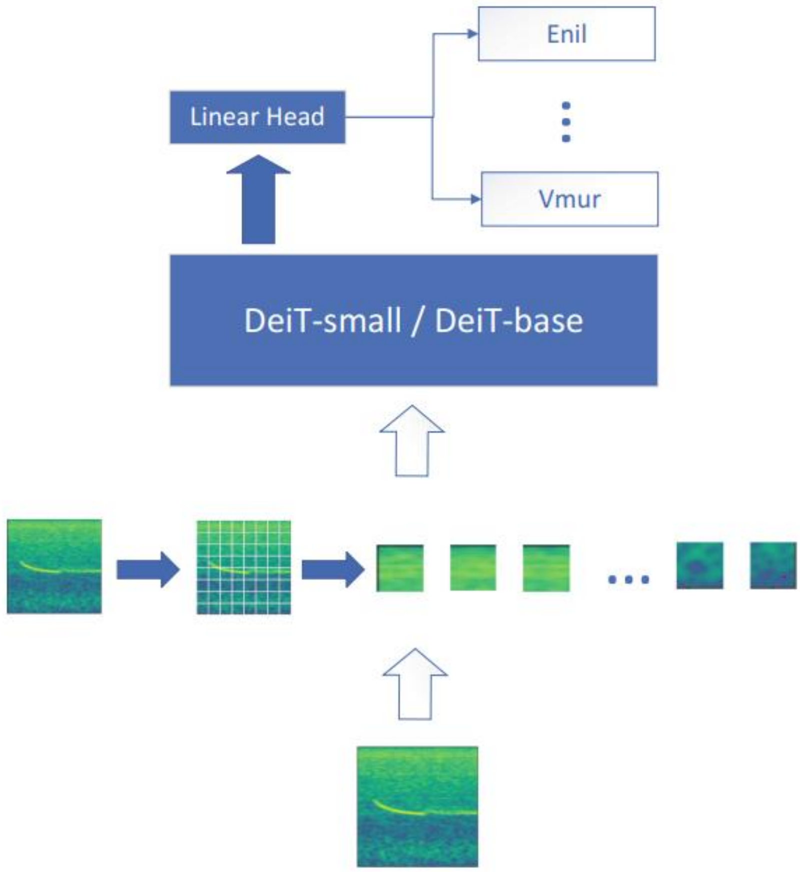

Figure 3.6: Workflow for bat species recognition

Our recognition workflow is shown in Figure 3.6. To train our model, we first extracted echolocation calls from the Tierstimmenarchiv data set using our detection approach.

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[14] https://www.tierstimmenarchiv.de/

For this purpose, the detection model was fine-tuned to the audio recordings of the Tierstimmenarchiv. We selected 90% as the threshold at which a detection is accepted. During training, we generate 128-dimensional log Mel filter bank features computed by applying a 23 ms TE Hanning window with a frame shift of 2.5 ms TE. We place each call in the midst of a 330 ms TE window, which results in an input resolution of 128 × 128. For the recognition task, we selected a deeper architecture to match the complexity of the task. We used two pre-trained data-efficient image base transformers (DeiT-small and DeiT-base) as alternatives. Both architectures consist of 12 layers as in DeiTtiny, but DeiT-small has 6 self-attention heads per layer and DeiT-base has 12 self-attention heads per layer, whereas DeiT-tiny has only 3 self-attention heads per layer. Each image is then split (as in the detection workflow) into 16 × 16 patches with a stride of 10 in both dimensions, which results in 144 patches in this configuration.

3.3.4 Experiments

In this section, our methods are evaluated on different data sets. First, we describe the applied quality metrics as well as the used data sets in Sect. 3.3.4.1 and Sect. 3.3.4.2, respectively. Afterwards, we present our bat call detection results and the conducted experiments for bat species recognition in Sect. 3.3.5. In all experiments, a workstation equipped with an AMD EPYCTM 7702P 64-Core CPU, 256 GB RAM, and four NVIDIAR A100-PCIe-40GB GPUs were used. We implemented our approach using the PyTorch deep learning framework (Paszke et al. 2017), utilizing the Torchaudio library (Yang et al. 2022) for audio and signal processing. The pre-trained DeiT models are available in the PyTorch Image Models (timm) library (Wightman et al. 2022).

3.3.4.1 Quality Metrics

To evaluate the performance of our bat call detection approach, average precision (AP) and recall at 95% precision are used as our quality metrics. The AP score is the most commonly used quality measure for retrieval results and approximates the area under the recall-precision curve. The task of bat call detection can be considered as a retrieval problem where the annotated bat calls represent the relevant documents. Then, the AP score is calculated from the list of ranked documents as follows:

$$AP(\rho) = \frac{1}{|R \cap \rho^N|} \sum_{k=1}^{N} \frac{|R \cap \rho^k|}{k} \psi(i_k), \tag{1}$$

$$\text{with} \quad \psi(i_k) = \begin{cases} 1 & \text{if } i_k \in R \\ 0 & \text{otherwise} \end{cases}$$

where N is the length of the ranked document list (total number of analysed audio snippets), ρk = {i1, i2,...,ik} is the ranked document list up to rank k, R is the set of relevant documents (audio snippets containing a bat call), R ∩ ρk is the number of relevant documents in the top-k of ρ and ψ(ik) is the relevance function. Generally speaking, AP is the average of the precision values at each relevant document.

To determine whether the model underestimates the number of bat calls in the test set, we further calculate recall at 95% precision, i.e., only 5% of false positives are allowed for this metric. To evaluate the performance of our bat call recognition approach, we use the accuracy metric as well as the F1-score. These metrics are widely used for evaluating classification models.

3.3.4.2 Data

Altogether, three different data sets are used as our test material for the detection task: two data sets provided by the Indicator Bats Program (iBats) (K. E. Jones et al. 2013) and a third data set provided by the Norfolk Bat Survey (Newson, Evans, and Gillings 2015). They consist of time-expanded ultrasonic acoustic data recorded between 2005 and 2011.

Table 3.6: Overview of the data set used for bat species recognition, showing the distribution of bat species including the number of recordings, the duration and the number of detected calls per species.

Species	Code	Recordings	Duration (s)(TE)	Detected calls
Eptesicus nilssonii	Enil	26	778	557
Eptesicus serotinus	Eser	75	2,018	1,926
Myotis brandtii/mystacinus	Mbart	24	1,770	2,033
Myotis dasycneme	Mdas	69	1,557	1,613
Myotis daubentonii	Mdau	128	3,370	4,764
Myotis emarginatus	Meme	28	450	597
Myotis myotis	Mmyo	52	1,202	1,598
Myotis nattereri	Mnat	77	1,969	2,714
Nyctalus leisleri	Nlei	78	2,338	1,770
Nyctalus noctula	Nnoc	95	3,236	2,574
Pipistrellus kuhlii	Pkuh	138	3,655	3,493
Pipistrellus nathusii	Pnat	140	3,760	3,279
Pipistrellus pipistrellus	Ppip	267	6,696	6,484
Vespertilio murinus	Vmur	69	1,788	1,654
Σ		1,266	34,587	35,056

Table 3.7: Number of recordings and bat calls per test set used for bat call detection.

Test set	Number of recordings	Number of calls
iBats R&B	500	1,604
iBats UK	434	842
Norfolk	500	1,345

The number of recordings and bat calls per test set are summarized in Table 3.7. We used 2,812 recordings containing 4,782 calls for training; these are a subset of the iBats R&B data collection. The described training and test split matches the one used by Mac Aodha et al. (2018). Following Schwab et al. (2022), we use a data set provided by the Tierstimmenarchiv for the recognition task. The data was originally recorded by Skiba (Skiba 2003) and later digitized. The mono audio files were provided in the WAV format with a sampling rate of 96 kHz and a bit depth of 24. Table 3.7 shows the amount of data per class along with the number of detected calls. As mentioned in Sect. 3.3.3.2, we first extracted these calls using our detection model. Although the annotations are given only per file, it is viable to assume that all detected calls in a certain recording belong to the corresponding manually annotated class of the file. This procedure is applicable because the data recorded by Skiba consists of high quality active recordings, i.e., the bats were captured for the recording and were close to the microphone.

Table 3.8: Summary of the training settings for the detection and recognition models

Hyperparameter	Detection	Recognition
learning rate	$5e^{-5}$	$1e^{-4}$
warm up	✓	✓
optimizer	ADAM (Kingma and Ba 2014)	ADAM
batch size	64	64

input resolution	128 × 64	128 × 128
time/frequency masking	✓	✓
patch stride	10	10
random noise	✓	✓

Table 3.9: Bat call detection results on three different datasets and comparison to state-of-the-art approaches.

Average Precision				
Testset	Method			
	Random Forest	CNN_{FAST}	CNN_{FULL}	DeiT-tiny
iBats R&B	0.674	0.863	0.895	**0.900**
iBats UK	0.648	0.781	0.866	**0.902**
Norfolk	0.630	0.861	0.882	**0.898**
Recall at 95% precision				
iBats R&B	0.568	0.777	0.818	**0.821**
iBats UK	0.324	0.570	0.670	**0.681**
Norfolk	0.049	0.781	0.754	**0.801**

3.3.5 Results

Bat Call Detection. As mentioned above, our bat call detection model is trained using 2,812 recordings containing 4,782 calls. To augment the data, three different time crops were sampled per call, which contain the call or part of the call. For each call, six negative crops were randomly sampled, so that the overall training set contains 14,346 positive samples (bat call) and 28,692 negative samples. Furthermore, data augmentation techniques for spectrograms introduced by Park et al. (2019) for speech recognition were used (Park et al. 2019), such as time and frequency masking. The training settings are summarized in Table 3.8.

We adopted the evaluation protocol used by Mac Aodha et al. (2018). A detection is considered as a true positive if its distance to the ground truth is smaller than a given threshold. We used a threshold of 100 ms TE, similar to Mac Aodha et al. (2018). Table 3.9 summarizes the results of our approach and compares them to state-of-the-art approaches. The results of the random forest approach, CNNF AST and CNNF ULL are reported by Mac Aodha et al. (2018). Our self-attention approach outperforms the other approaches on all three data sets.

Table 3.10: Comparison of bat call classification results of the DeiT-base model using call-based and recording-based splits of the data set.

Species	F1-Score	
	Call-based split	Recording-based split
Enil	0.99	0.75
Eser	0.99	0.82
Mbart	0.99	0.95
Mdas	1.00	0.80
Mdau	0.99	0.92
Meme	1.00	0.98
Mmyo	1.00	0.98
Mnat	1.00	0.93
Nlei	0.99	0.76

Nnoc	1.00	0.91
Pkuh	0.99	0.86
Pnat	0.98	0.78
Ppip	0.99	0.94
Vmur	1.00	0.79
Avg	0.99	0.87

Table 3.11: Recognition results

Method	Accuracy
DeiT-base + Log-Mel-Spectrogram	**0.887**
DeiT-small + Log-Mel-Spectrogram	0.882
ResNet-50 + Log-Mel-Spectrogram	0.884
DeiT-base + Log-Spectrogram	0.881
ResNet-50 + Log-Spectrogram	0.879

The model was trained for a maximum of five epochs. While the training took about 146 s per epoch, the average inference runtime is 0.093 s for an audio signal with a length of one second using the hardware/software system described at the beginning of Sect. 3.3.4.

Bat Call Recognition. In this section, we evaluate our bat call recognition model. We compare our self-attention approach to the ResNet-50 architecture that was used by Schwab et al. (2022). Additionally, we evaluate the use of LogSpectrograms vs. Log-Mel-Spectrograms. Furthermore, we show that the way we split the data set into training and test data has a great impact on the result.

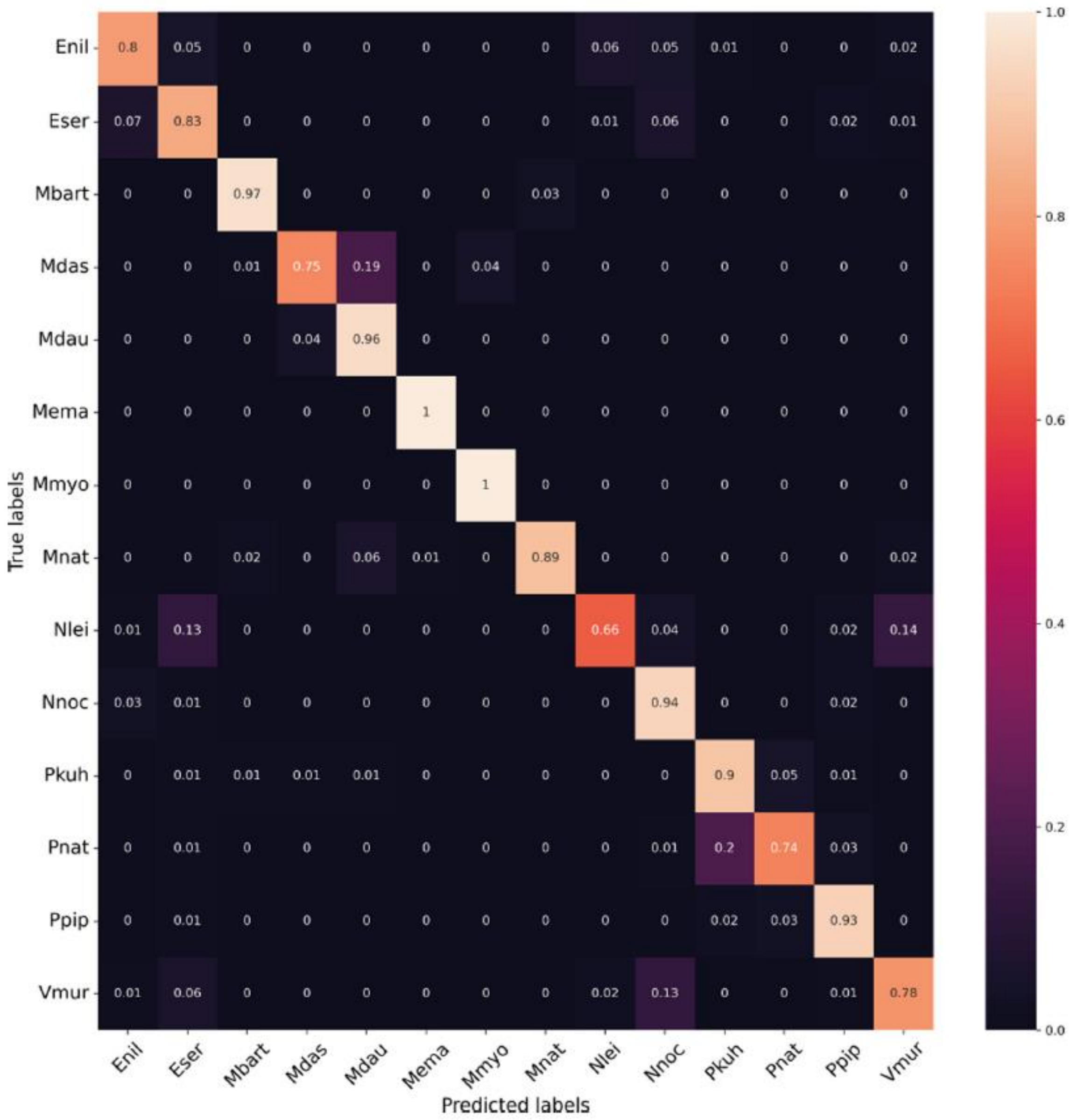

Figure 3.7: Normalized confusion matrix of the bat species classification results.

First, we follow the split described by Schwab et al. (2022), where 20% of all echolocation calls are used for evaluation, meaning that different calls emitted by the same individual in the same call sequence can be found in both the test and the training set. Since these calls are very similar, this approach is prone to overfitting and leads to inflated performance values. To better evaluate the generalization capabilities of the model, we split the data set on a recording level. For each class, we use 20% of the files for testing and all remaining files for training to provide a more appropriate evaluation strategy. Table 3.10 summarizes the results using both splits.

Indeed, the evaluation using a call-based split reaches very high F1-score values (≥0.98) for all species, which is consistent with the findings of Schwab et al. (2022). In contrast, these excellent scores cannot be confirmed using a file based split of the data set. However, our model still reaches very good results on this test split, since no class drops below 0.75, as Table 3.10 confirms. Therefore, we will use the latter, more meaningful data set split in the remainder of this paper.

In the following, we compare two transformer architectures, namely DeiTbase and DeiT-small, with the ResNet-50 CNN architecture. With 6 self-attention heads per layer, DeiT-small is a compromise between DeiT-tiny (3 heads) and DeiT-base (12 heads). As our input, we use both Log-Spectrograms as well as Log-Mel-Spectrograms. Table 3.11 shows that we achieve better results than the ResNet-50 on both kinds of spectrograms. Furthermore, our best model, i.e., DeiT-base, achieves a 0.6% higher accuracy using Log-Mel-Spectrograms than using simple Log-Spectrograms.

Next, we consider the results of the best model (DeiT-base with Log-MelSpectrograms) for individual bat species. For this purpose, the confusion matrix of the classification model is visualized in Figure 3.7. The matrix shows a distinct diagonal line, which confirms the good classification results. Furthermore, it reveals that test samples are often mistaken for another species of the same Genus. For instance, the model tends to confuse Enil and Eser, Mdas and Mdau or Pkuh and Pnat. Many confusions that span across two different Genera are quite difficult to distinguish as well, e.g., the bats of the Nyctaloid group (Nlei, Nnoc, Eser, Enil, Vmur) (Paumen et al. 2021). Most of the mistakes made by the model concern species that are hard to distinguish even for human experts, and the model predicted the higher order class correctly.

The recognition model was trained for a maximum of 50 epochs. While the training of the DeiT-base model took about 413 s per epoch, the average inference runtime is 0.02 s per bat call using the hardware/software system described at the beginning of Sect. 3.3.4.

3.3.6 Conclusion

We presented a novel self-attention approach for detecting bat echolocation calls and recognizing bat species in audio spectrograms. It is based on pre-trained data-efficient image transformer models used as components in a workflow that we developed to process audio spectrograms of recorded bat echolocation calls. We showed that it outperforms state-of-the-art CNN-based approaches for bat call detection as well as for bat species recognition on several publicly available data sets, yielding up to 90.2%

average precision for detection and up to 88.7% accuracy for recognition, respectively. Furthermore, we demonstrated that the distribution of the training and test set is important for determining the recognition accuracy.

Our neural network models for bat echolocation call detection and bat species recognition are made publicly available to other researchers. There are several areas of future work. First, the detection performance could be improved by considering different call durations and different types of calls, like social calls and feeding buzzes, and using a special kind of object detection network architecture. Second, the generalization capabilities of the trained neural network models should be further investigated by considering, for example, different hardware devices and recording environments. Finally, the classification of bat behaviour and the recognition of individual bats based on different echolocation calls are interesting research directions in the future.

Acknowledgement

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Research dimension 3:

Potential for a successful transfer of the tRackIT-system into conservation practice

4. Introduction

The prerequisites for the successful transfer of conservation technologies into practice consist of defining the end users and their requirements, identifying and testing how and whether the offered product meets these requirements and regularly updating the technological solutions in feedback with the end users.

Among the technological developments presented herein, the tRackIT-system has the most significant potential for broad application in conservation practice, as it can be used for all species active above ground with a body mass above 2g and there is a great need for automation of the tracking technology for small species. Within the scope of this thesis, the transfer of the tRackIT-system into conservation practice is demonstrated for two use cases that also represent different user segments in terms of aims and funding.

4.1 Application of the tRackIT-system for the protection of meadow-breeding birds: The curlew (Numenius arquata) in Bavaria.

The population of the curlew (Numenius arquata) has been declining steadily throughout Germany since the 1970s - particularly sharply in southern Germany (Grüneberg et al. 2015). With less than 500 breeding pairs in Bavaria, the curlew has been in Category I on the Red List of endangered species for years and is in acute danger of regional extinction (Fünfstück, von Lossow, and Schöpf 2003). The lack of reproductive success is the main cause of the decline in meadow breeding bird populations (Roodbergen, van der Werf, and Hötker 2012). Intensively used grassland, drainage, and predation by ground predators are the main factors for high chick mortalities proven so far (Franks et al. 2018; Donal, Gree, and Heath 2001). The breeding success of the curlew is worryingly low in many areas of Bavaria (Salewski et al. 2020). In 2015, for example, 37 pairs in an area specifically designated for the protection of meadow-breeding birds - the Wiesmet - produced only a single offspring.

The “Landesbund für Vogelschutz” (LBV), one of the oldest nature conservation NGOs in Germany, is cooperating with the Bavarian State Office for the Environment (LfU) and the nature conservation authorities to find out more about behaviour and breeding ecology of this species in order to enhance its protection. Since 2019, a project has been running in the Altmühl Valley (Bavaria, Germany) in which juvenile curlews are equipped with radio telemetry transmitters in order to gain better knowledge about their whereabouts and the behaviour of the bird families. With the help of the transmitters, protection measures have taken effect and, for the first time since 2008, population-sustaining breeding success has been achieved. For example, through consultation with farmers, mowing meadows where curlew chicks are currently residing is postponed to protect them from being killed.

In addition to the manual VHF-telemetry conducted so far, tRackIT-Stations, which enable automatic tracking and live transmission and visualisation of the recorded data, are being tested in the field since 2021[15],. Activity patterns can be derived from the received data and any transmitter losses or mortality events can be immediately detected.

One of the major breakthroughs in avian ecology and conservation research was the development of Mayfield´s daily nest survival model (Mayfield 2016) developed to deliver a less biased estimate of the probability that a nest will produce at least one new adult individual than previous methods. However, one implicit assumption of Mayfield's estimator was that the date of death of chicks is known exactly- an assumption that is often violated in field studies with limited capacities to control individuals on a daily basis (Dinsmore, White, and Knopf 2002).

The tRackIT-system records the signals of the chicks several times a minute and increases the accuracy of the measurements compared to the complex, labour-intensive handheld telemetry. In the presented use case the tRackIT-system enabled researchers to narrow down the timing of mortality, e.g. due to predation events, to a few seconds, and patterns in the recorded signals also allowed for a good estimate of the reason for death (Figure 4.1).

[15] https://www.audi-umweltstiftung.de/umweltstiftung/en/projects/greenovation/telemetry-technology.html

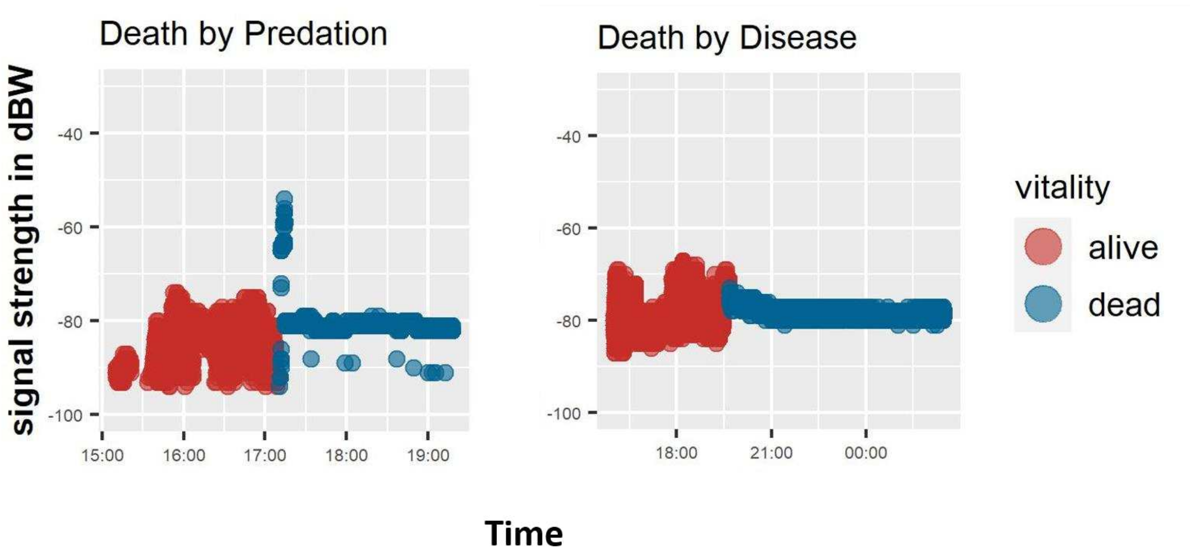

Figure 4.0.1: VHF-Signal pattern at the time of death of a Curlew chick killed by an avian predator (left) and an oystercatcher chick that died from an unknown disease

This facilitates the calculation of the temporal variation in nest survival with an unprecedented temporal resolution.

As a result, the tRackIT-system has already been deployed at the northern Sea to investigate nest survival of oystercatchers[16] where it facilitated the early detection of an outbreak of a still unknown sickness among wader chicks in northern Germany.

Figure 4.1 shows the exemplary signal pattern of two wader chicks of which the left one was predated. The sudden peak in signal strength suggests that the chick was lifted out of the meadow and killed by an avian predator. The sudden inactivity of the chick on the right side, indicated by low variation in the signal strength (see Section 3.2), suggests either death or transmitter loss without predator interaction. The chick carried a temperature-sensitive transmitter and body temperature also dropped at the same time as the inactivity started. It was found dead the same day without injuries. Samples given to the laboratory were not analysed at the state of the submission of the thesis. However, seven additional chicks in the same area died the same way, which makes a yet unknown disease the most likely cause of death. In both cases, the timing of death could be narrowed down to a few seconds.

[16] https://bergenhusen.nabu.de/forschung/austernfischer/index.htm

In the next few years, the tRackIT-system will also be deployed in other protection areas for meadow-breeding birds in Bavaria and at the northern sea.

4.2 Application of the tRackIT-system to assess the potential disturbance and destruction of bat habitats prior to the construction of wind turbines

Climate change and the internationally agreed climate objectives demand the rapid conversion of the electricity sector towards renewable energies. In order to achieve the goal of covering 85% of German electricity consumption by renewable energies by 2030, an installation of 25 to 38 wind turbines per week will be necessary starting from now (Minister of Economic Affairs Robert Habeck, German Parliament 2022-01-13).

It is mandatory in most construction projects to survey the occurrence of protected animal species in an environmental assessment to determine the impact of the intervention on the local conservation status prior to construction (§ 42 para. 1 no. 1 BNatSchG). In particular, the investigation of bats and their space use causes a considerable survey and evaluation effort and regularly leads to a delay in the assessment process by several months to years. The reason for this is not least the lack of digitalization and automation of the methods used.

In the practical implementation of an environmental assessment, minimum distance thresholds of construction sites to protected objects such as foraging areas or resting and reproduction sites of bats are usually specified by the legislator or within assessment guidelines (usually 200 - 300 m). To prevent the loss of essential hunting grounds as well as roosts, bats are captured with nets and equipped with radio telemetry transmitters. Using directional antennas, roosts are detected during the day, and by means of cross-direction finding, the foraging sites of the animals are determined at night. These methods are labour-intensive and therefore costly, and the quality of the collected data depends on the staff performing the survey. Projects currently require that five individuals be radio-tracked over five nights if a bat colony is discovered in the study area. This means that a minimum of two persons must track tagged bats for a total of 25 full nights (~500 person-hours) per colony per planned wind farm to determine their locations throughout the night. The number of expected colonies is unknown in advance of planning (Hurst et al. 2015).

In addition to the labour-intensity, the method has hardly changed since the 1960s (Cochran et al 1962) and the susceptibility to errors exceeds tolerable limits. Acceptable results with a localization error < 100 m to the actual position of the individual can only be achieved if the workers are optimally positioned with respect to the tracked individual. Optimal positioning, in this case, means that the distance to the animal should be as small as possible and the intersection angle of the bearings of the operators should approximate 90°. Otherwise, the spatial error quickly escalates to several hundred meters and is thus significantly larger than the distance threshold that leads to the exclusion of a plant construction site (Figure 4.2). Tracking fast and long-distance flying animal species in poorly accessible terrain (forests in the highlands) regularly results in suboptimal positioning.

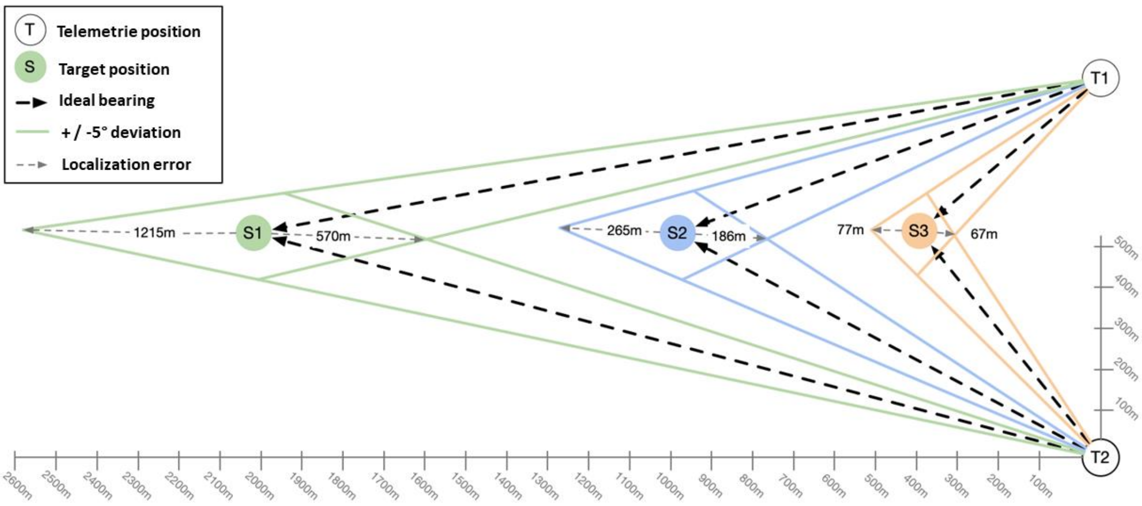

Figure 4.2: Localisation error caused by +/-5° bearing error, intersection angle and distance to the target.

4.2.1 Automatic presence-absence telemetry of bats to estimate potential disturbance and destruction due to wind farm construction

An adaptation of the tRackIT-system collects impact-related space utilization data over the entire recording season (April to October), transmits it via LTE, visualizes it, and evaluates it automatically (Figure 4.3). For this purpose, the signal strength of the received radio signals is set in relation to distance, allowing the distance of the location of the tagged animal to the site of the intervention to be recorded accurately and with very high temporal resolution (1 data point per second). By reducing the tRackIT-system to one station with only one omnidirectional antenna per investigated construction site, compared to multiple stations with 4 antennas each, as required for the previously developed triangulation method, the amount of work and material required in the context of environmental assessments becomes feasible.

The collected data are immediately transferred to the tRackIT online service for further analysis. Statistical evaluation procedures, specifically developed algorithms, as well as the visualization of the available data are used to present interim results to the experts already during the ongoing planning procedure. For example, the approximation of observed individuals at different hours of a day can be used for the assessment of potential disturbances, i.e. a close location during daytime hours can be used to infer the presence of roosting trees. If only temporary nocturnal approaches can be detected, it is very likely that the observed individuals are hunting. If no or only very weak signals are recorded, it can be assumed that there is no disturbance for the individual and in total for the local population of the species.

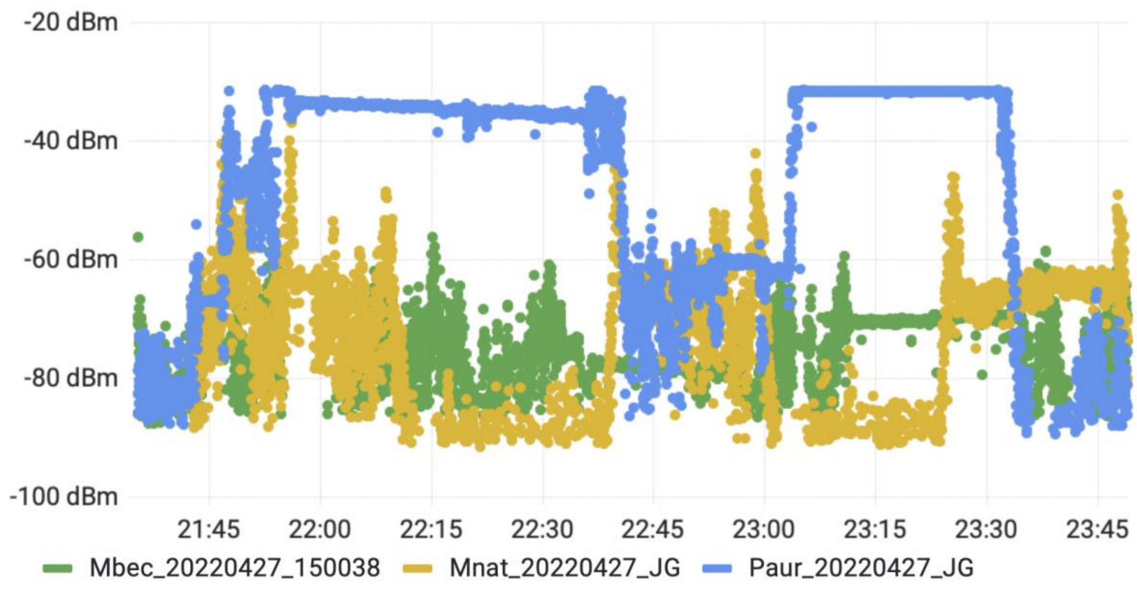

Figure 4.3: Live-view of 3 bat individuals recorded at a tRackIT-station.

The working time for radio-tracking in a wind farm is thus limited to 2 hours of set-up and dismantling per station (20 hours of work for a large wind farm with 10 planned turbines) and occasional maintenance work, which can be carried out in parallel with other fieldwork. The labour-time is also independent of the number of bat colonies detected and is much easier to calculate compared to 500 person-hours of labour per colony with an uncertain number of colonies.

4.2.2 Demonstrator test

As part of the preparation of an environmental report for a wind farm with 6 planned turbines, 6 demonstrators of tRackIT-stations were deployed at the planned turbine locations over a period of 5 months. Initial tests show a distance accuracy of the method of fewer than 30 meters (Figure 4.4).

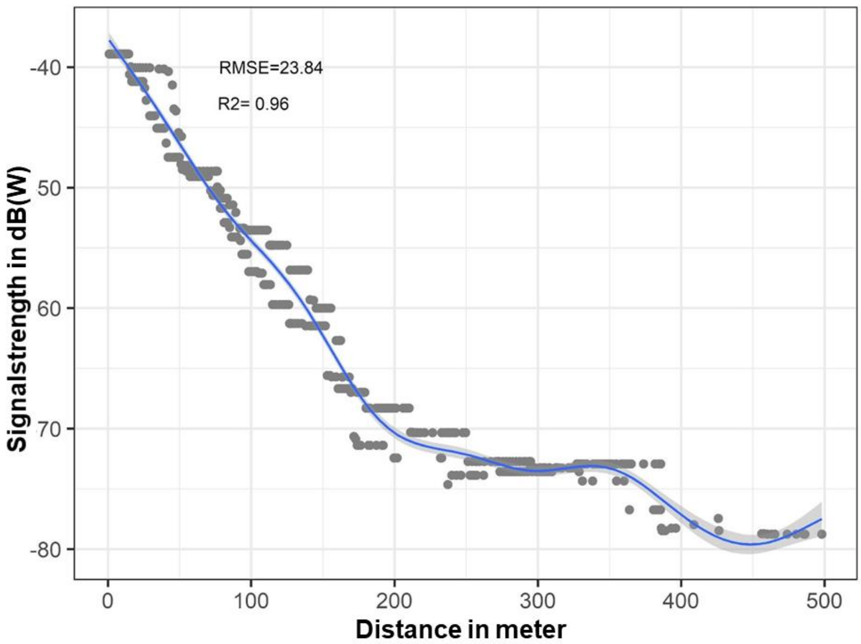

Figure 4.4: Signal strength in relation to distance to the tRackIT-station.

For comparison with the established method, the roosts of tagged bats were still searched manually and their movements were tracked overnight by workers in the field. The evaluation of the results from the roost search shows that the tRackIT stations reliably and continuously record the use of roost trees in the critical distance range around the planned facilities (99% of the cases) with sufficient spatial accuracy (Figure 4.5). Foraging activity within the critical radius around planned construction sites was also reliably recorded (Figure 4.6).

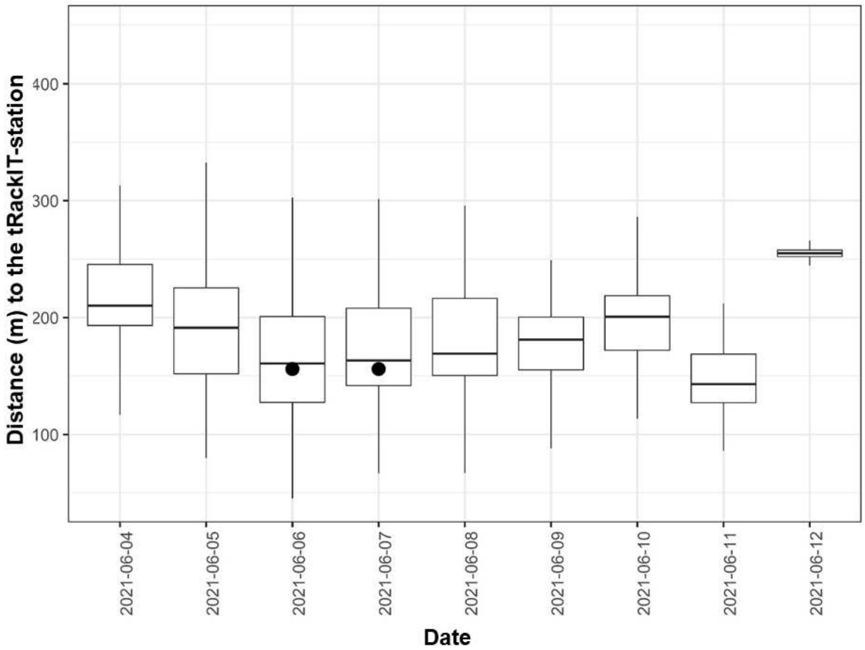

Figure 4.5: Measured distances during daytime based on signal strength (boxplots) and actual distance of the roost (black dots)

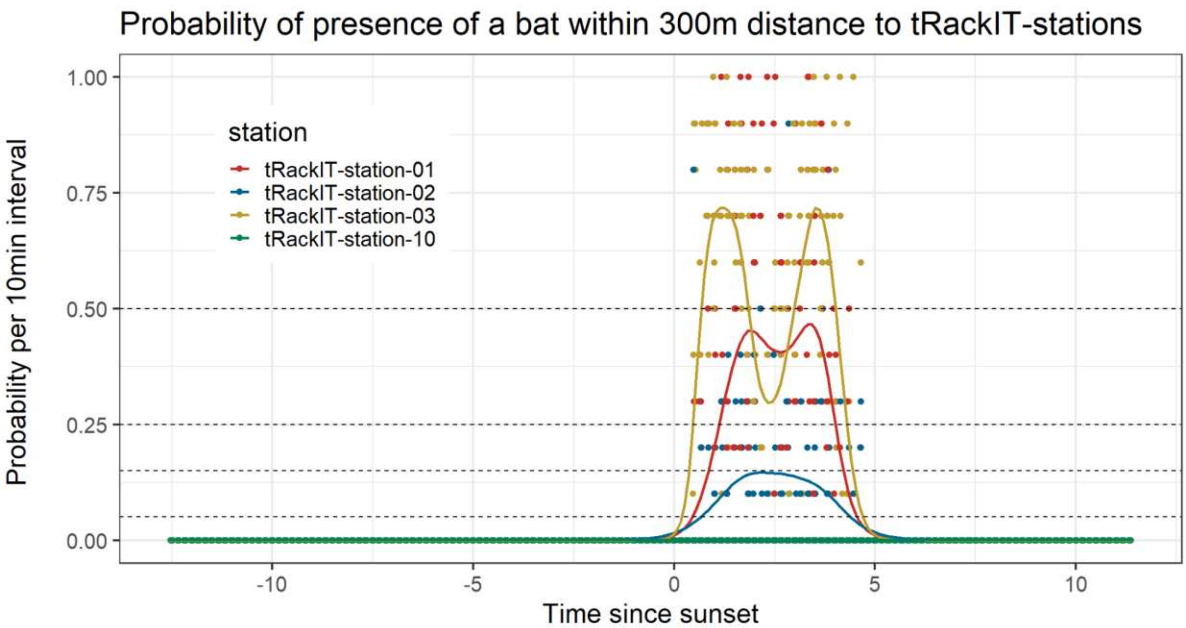

Figure 4.6: Probability of presence of an endangered bat species (Barbastelle bat) within a critical radius of 300m to planned construction sites. Stations 1, 2, and 3 are within or close to a foraging site of the bat. Station 10 is not affected.

The comparison with manual telemetry showed that the established method measured positions within a 300 m radius of the planned sites that could not be confirmed by the tRackIT stations. An assessment based solely on the manual method would incorrectly exclude these locations from the planning.

4.2.3 Users' feedback and conclusion

The feedback of the users confirm the assumption that especially the live data transmission facilitates the assessment practice considerably. The advantages of the method can be summarized as follows:

- Significant reduction in workload, allowing more study areas per season to be systematically and reproducibly investigated.
- High transparency and reduction of quality fluctuations through standardization; increased juridical security of expert opinions.
- Differentiated, detailed, and thus precise nature and species protection risk assessments.
- Massive reduction of personnel effort and costs: 500 person-hours per bat colony compared to a few hours of installation of the stations.
- Early detection of planning obstacles; timely adjustment of the planning process; site optimization.
- Reduction in time between data collection and reporting

The quality of the collected data as well as the already emerging potential for simplification and acceleration of the processes has led the involved experts to see the method as the upcoming industry standard.

Research dimension 4:

Strategies to ensure sustainable access to developments and continued technical support

5. Strategies to ensure sustainable access to developments and continued technical support

The regular chain of development and distribution for e.g. consumer market technology consists of ideation, research and development, production, and, finally yet importantly, support for users that involves services like warranty, repairs, and training and the implementation of user's feedback in new product versions (Lahoz-Monfort et al. 2019). In conservation technology the chain of production often breaks after the research and development phase, leaving potential users with either no or technically challenging information, and at best sporadic support for reconstruction and implementation.

This may be caused by a lack of interest of academic developers or conservation organizations to turn their innovations into finalized commercially or open-source available products after projects have expired and scholars have moved on (Speaker et al. 2022; Hahn, Bombaci, and Wittemyer 2022). Those Projects that attempt to scale-up technology, commercially or non-commercially, often prove not to be viable due to lack of funding or over-estimated open-source contributions (Iacona et al. 2019; Lahoz-Monfort et al. 2019).

The tRackIT-Systems company: ensuring long-term availability and technical support

The foundation of a company that offers support, feeds back with users to improve the products, helps with technical difficulties, and guarantees access to the products, has proven to be an appropriate solution to offer a longer-term perspective to the conservation community (Iacona et al. 2019). The foundation of the tRackIT-Systems company, which dedicates itself to the development of smart technological solutions for environmental monitoring, will ensure long-term access to existing and upcoming conservation technologies, and provide continued technological support to conservation practitioners.

One of the problematic developments often observed following the commercialization of conservation technology products is a significant increase in prices caused by a relatively small market. As a result, access to the technologies is often blocked for poorly financed conservation practitioners. This is particularly problematic considering the unequal distribution of financial resources, which on top contradicts the distribution of biodiversity across the globe (Waldron et al. 2013).

The implementation of the tRackIT-system as a tool for meadow-breeding bird conservation, has proved to be a success in terms of workload reduction and knowledge gain. However, it also showed that the financing of projects is the biggest hurdle for non-profit organizations. Thus, this use case represents the often poorly funded community of conservationists, without whose activities and commitment practical species conservation would be virtually non-existent. In order to guarantee access to these stakeholders, pricing the services of the tRackIT-Systems company can only cover the costs incurred and not generate a profit. From a purely economic perspective, serving this customer segment is unprofitable. However, the goal of the tRackIT-Systems company is to make its achievements available to the entire conservation community.

The second use case concerns the assessment of potential violations of the European nature conservation act caused by disturbance and destruction of bat habitats due to the construction of wind turbines (subsection 4.3). Large energy companies usually commission these investigations. Even if the service offered by the tRackIT-Systems company is priced at a relatively high level, the automation of the processes still means a significant cost reduction compared to the costs previously incurred for manual recording methods.

The business idea of the tRackIT-Systems company currently focuses on the recording and protection of bats in connection with the expansion of wind energy. However, in order to keep access to technologies open to all conservation stakeholders, the tRackIT-Systems company intends to cross-fund the support for the implementation of projects in less well-funded areas of conservation by the provision of services in well-funded market segments.

To support the founding of the tRackIT-Systems company a 12-month financial grant (EXIST: University-Based Business Start-Ups) will be provided by the German Federal Ministry for Economic Affairs and Climate Action for one year from 2023.

Conclusions

6. Conclusions

This work aimed to identify the needs for the development of sensors and data analysis tools, based on close collaboration between computer scientists, conservation practitioners, and ecologists, which would lead to real improvements in research and practice and allow knowledge gaps in research to be filled. Monitoring individuals of small species was identified as a key challenge.

Common problems arise when observing small animal species in densely vegetated areas. Individuals are difficult to recognize by human observers and the continuous observation of even only one individual at a time is close to impossible. Currently available technical solutions such as GPS transmitters or camera traps fail for small species.

The overall objectives of this work were to develop tailored sensory solutions for monitoring individuals of small species (research dimension 1), to provide easy-to-use data analysis tools (research dimension 2), to test the suitability of the developments for use in conservation applications with different research questions (research dimension 3). In addition, access to the developments should be ensured in the form of implementation support beyond the usual period of academic project duration (research dimension 4).

In the following, the achievement of the sub-objectives of the respective goals as well as opportunities and challenges are discussed.

6.1 Sensors (research dimension 1)

In addition to the question of what type of data should be collected, there were several design requirements for the sensors that needed to be met to ensure their usefulness in the field. The sensors should be cost-effective, easy to use, operate autonomously over a long period (several months), automatically record the data and transfer it in real-time to a remote server. This means that the components had to be as cheap as possible, the construction of the devices had to withstand harsh weather conditions, the power supply had to be guaranteed even at locations with partial shading, and the recording of data had to be limited to events of interest to reduce the changing of storage media and the amount of data to be transferred, and analysed to a minimum. Last but not least, the application range should be as broad as possible. Two developments were presented in this work, that fulfil the above-mentioned criteria.

The tRackIT-system was designed to permanently record signals emitted by VHF-transmitters attached to animals to analyse their movements, behaviour, and physical conditions in real time. Existing systems are either not open-source, costly, and require a high level of technical expertise, or crucial functionalities such as localisation or live data transfer have not been realised. The tRackIT-system closes this gap.

The hardware design and software, optimised over the research period, together with the live data transfer on the status of the stations could reduce the maintenance interaction to a minimum, thus achieving a real reduction in the workload while at the same time improving the quality of the data. The application of the system under harsh weather conditions such as at the northern sea showed its robustness in the field.

The tRackIT-system thus represents an important contribution to developments in the field of conservation technology. However, several fields of future work remain. It has been shown that the quality of the data depends strongly on the spatial structure of the station network. It is still pending to identify the parameters that constitute an optimal set-up to be able to apply these rules to new localities. Not all locations have access to the internet, therefore alternative solutions for the transmission of data have to be found. For small data rates, such as the transmission of status information, the problem has already been solved using LoRaWAN. However, this protocol is unsuitable for the transmission of VHF signals.

The BatRack incorporates three different types of sensors that work together to reliably record audio, video, and radio tracking data of tagged individuals as well as detailed observation of the behaviour of non-tagged individuals. While the tRackIT-system is designed to continuously record VHF data even at greater distances, the BatRack is suitable for recording the occurrence of animals and detailed behavioural recordings of them at selected positions.

The BatRack hardware is based on the developments of the tRackIT-system and the software is an enhanced version of tRackITOS. Therefore, both the robustness under harsh weather conditions and the reliability, as well as the functionality of the software, are comparable, with the limitation that the transmission of data via LTE is unsuitable for sound and video recordings due to their size.

In two use cases, the usefulness of this tool was demonstrated, especially for the visual observation of behaviour that is otherwise difficult to observe. First, the BatRack was used as a tool to create a ground-truth dataset for training the activity classification model. For more than 700 hours, the behaviour of a total of 25 individuals from two bat species had been recorded. Particularly concerning the observation of tagged individuals, it could be shown that the system is also transferable to other animal species.

In addition, the BatRack was used to study a behaviour that has been rarely investigated so far. Bats are known to display a specific behaviour called dawn-swarming consisting of overflights around the roosting tree followed by multiple landings and leaps from the roost entrance, often accompanied by vocalizations before bats finally enter the roosts or move on (Vaughan and O'Shea 1976; Russo, Cistrone, and Jones 2005). Although this behaviour is considered to play a central role in the social communication of bats, especially concerning the selection of day roosts (Kunz 1982), research on temporal pattern and dynamics are scarce. An intensive literature search resulted in a total of two articles, both by the same authors, in which the behaviour was investigated for one species in one region (Naďo and Kaňuch 2015, 2013).

We used BatRacks to study temporal patterns in the dawn-swarming behaviour of *Myotis bechsteinii* and were able to show that this behaviour is not restricted to the time before sunset but is performed throughout the night.

The two use cases show that the BatRack is a useful tool to realize the spot observation of specific behaviours. In conservation practice, it could be deployed, for example, for automated population counts at known bat trees at the time of emergence or for checking the acceptance of crossing aids over motorways. However, the potential application of BatRack is narrower and more focused on bats than that of the tRackIT-system, which is why no transfer to conservation practice was achieved in the course of this study.

6.2 Data analysis tools (research dimension 2)

To facilitate the processing of the high amounts of collected data into analysable products various functionalities and tools were developed throughout this research project.

The programming language and statistical software R has grown to be one of the most commonly used tools for the processing and analysis of ecological data. It can now be assumed that most scientists and students in the field of environmental sciences have at least a basic knowledge of how to use it. The applicability of a commonly understood programming language greatly facilitates the reproducibility of results and the sharing of functionalities (Lai et al. 2019). Algorithms and functionalities for the processing of the raw data collected by the tRackIT-system, that enable the calculation of localisations or physical properties of the tagged individuals were made available as an R-package which also provides a standard data structure to facilitate the exchange of research projects. The same functionalities are also made available as a live service, including their visualization via Grafana, enabling real-time monitoring of movement, physical state, and behaviour.

Various machine learning and deep learning algorithms are now available to researchers, often readily trained for specific tasks such as species recognition in camera trap data or acoustic recordings (Christin, Hervet, and Lecomte 2019). These readily trained AIs enable the application even for users who are not educated in this respect.

Here two machine learning approaches were presented of which the first allows the classification of behavioural states based on VHF-signal pattern (Chapter 3.2; Gottwald et al. (in review)). The second is a novel bat-call detection and classification tool that not only facilitates the detection and quantification of species-specific calls in audio recordings but also helps to narrow down the amount of acoustically triggered video recordings to those most likely showing a) a bat and b) a bat of a certain species (Chapter 3.3).

The former can significantly expand current boundaries in ecological research. Previous studies on bat activity rhythms were either carried out based on acoustic methods, which often do not allow species differentiation or a small number of individuals were tracked over a short period and with low resulting data density using manual radio telemetry. The method of behavioural classification presented here, based on patterns in the VHF signal, makes it possible to detect subtle differences between species, which in turn allow conclusions to be drawn about their ecological preferences.

The latter solves the problem of the large amount of data collected in the study of animals using visual sensors. The combination of a camera triggered by audio signals and a machine-learning model for the recognition of bat species in audio files not only enables the reliable visual recording of bats, but also the reduction of the videos to be viewed to files for which the target species was detected in the audio files at the same time. The effect of the analysis is comparable to automatic image recognition methods, with the advantage that species recognition based on images alone would be almost impossible for bats, but has been used for audio data for decades.

Some developments that would significantly expand the possibilities of the functionalities presented here are still pending. Five different triangulation algorithms have been implemented in the tRackIT R-Package as well as in the live-data analysis unit. Which of them performs best under which conditions still has to be investigated. The detection of further behaviours based on VHF signals, as is possible with accelerometers, for example, or the recognition of behaviours based on vocalizations, the detection of untagged individuals in video files, and their automatic counting are fields of future work.

The detection of anomalies for the automatic recognition of the time of death or changes in behaviour, such as the start of breeding or the birth of offspring, is possible in principle but has not yet been implemented. In addition, active work is being done on analysing the recorded data already on the devices in the field. Some of the authors involved in this work have presented solutions for the in-situ detection of bird species using edge computing. Comparable solutions are currently being tested for bats. The calculation of angles, positions, and behaviours on the receiver units themselves would also significantly reduce the mass of data to be transmitted and thus open up the possibility of real-time transmission using LoRaWan even in areas with poor network coverage.

6.3 Transfer into conservation practice and strategies for future accessibility of the developments (research dimensions 3 and 4)

Already at the development level, it could be shown that the tRackIT-system is broadly applicable and transferable to different taxonomic groups such as songbirds and bats. Other work has shown that even larger insects can be equipped with VHF transmitters (Fisher et al. 2021) so the existing research limits caused by the allowed ratio of body weight to transmitter weight could be considerably extended with this system. The two use cases presented in Chapter 4 confirmed that the tRackIT-system is suitable for a wide range of applications, which is key to the successful establishment of conservation technology.

In particular, the provision of high-level data products, which are now created and visualized directly on live data, opens up unimagined possibilities in conservation practice. Unusual changes in activity or a sudden drop in body temperature make it possible to determine the exact time of death of bird chicks, which significantly simplifies the determination of the cause of death. The permanent monitoring of the chicks' position helps to prevent them from being killed by mowing machines. In addition, the impact of planned interventions on the environment can be assessed at an early stage and planning can be adapted accordingly, thus saving time and money.

The accessibility of all presented developments is partly guaranteed by open-source publications of the hardware designs and software, and due to peer-reviewed papers. However, the use cases have also shown that the support by experienced experts in the deployment of the system is necessary in order not to jeopardize the success of the projects. The foundation of the tRackIT-Systems company is intended to secure this support in the long term.

6.4 Concluding remarks

A study published in the last year of this research project surveyed conservation practitioners, academic researchers, and technologists to assess the needs, barriers, and opportunities in conservation technology. It identified three main development requests for future tools: Automation, individual-level monitoring, and enhanced data processing.

Durability, low-cost, power efficiency, organized data management, and real-time data transmission were identified as the most important features that technological solutions in the field of conservation technology should bring to meet the requirements of real-world applications. Usability in terms of low technological knowledge required for the deployment of the tools together with continued technological support was identified as requirements for the establishment of new developments (Hahn, Bombaci, and Wittemyer 2022).

The developments presented in this thesis fulfil all these requirements and additionally extend them for application to small animals. The interaction of the sensor technology (research dimension 1) and the analysis tools (research dimension 2) forms a toolbox that makes it possible to collect and evaluate high-resolution data on the condition, behaviour, or movement of even small animals (<10g). By examining the practical applicability of the developments in terms of usability, stability in the field, and usability for various research questions (research dimension 3), this work already goes a step further than most academic development projects, which often only make the application potential of their developments a prospect. With the founding of the tRackIT-Systems company, the last of the requirements for conservation technology developments are also fulfilled - securing long-term access to the technologies and technological support for the implementation of future projects (research dimension 4).

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Expert-driven development of conservation technologies
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