Exploring social networks using vocal identity signatures

Individual recognition is the basis of all animal interactions, and this becomes especially important in species that have a dynamic social environment. Therefore, many gregarious animal species have evolved individually distinct signals. In this project we explore whether it is possible to automatically record, detect and classify individual vocalisation signatures to construct social networks of a free-living songbird, the zebra finches. Zebra finches are the best studied songbird in the laboratory, but we have only a rudimentary understanding of how, with whom, and why these birds vocalise in their natural environment. As individual song signatures of male zebra finches are classifiable by human observers, they offer an excellent study system to investigate the automation of the sound detection and identification process.

In this project we collect recordings of zebra finch vocalisations using automated sound recorders (Songmeters 3 and 4, Wildlife Acoustics, for more details see [1]) in their natural environment. With the use of detection and classification machine learning approaches, we aim to transform these extensive audio streams to meaningful information on which individual was where at which time. From this who/where/when-information we can then extrapolate a social network in the natural environment, allowing us to gain insight in the social organisation of this species.

If we can get this to work, this will be extremely exciting, as normally it is not feasible to follow birds in the natural environment without catching, marking, and (automatically) reobserving them in some way. Given that zebra finches (and individuals of many other species of potential interest) may only be around a particular area for a short time, due to e.g. nomadism, this proof-of-concept will constitute a relatively cheap alternative for tracking individuals of vocally active species.

Microphones

For recording the zebra finches, we used Songmeters (version 3 and 4, produced by Wildlife Acoustics). These are time-programmable sound recorders which can run for days on batteries, and until storage runs out when solar powered. To record zebra finches year-round, taking into account storage constraints, we scheduled recordings to take place one day from sunrise to sunset every four days. We also limited the sample rate to 16 kHz, as most frequencies of interest were below 8 kHz (the nyquist frequency). Recorders were put out near social hotspots, i.e. places where zebra finches tend to gather and hang out during the day (as shown by a recent paper from our group).

Social networks via vocal signatures

Raw data consists of 1-h long uncompressed .wav recordings which can contain 1 full hour of zebra finch vocalisations or 1 hour of wind noise and everything in between (see Figure 1). From these continuous audio streams, we want to isolate the vocalisations of interest, in this case zebra finch songs. We do this with the help of BirdNET. This software was developed for the detection of bird species in audio streams, and it has recently been updated (v2.4) to allow for recognition of custom classes. We have annotated the songs in 198 hours of audio that was collected using the same equipment. We will use these songs to train BirdNET to recognise our custom class 'zebra finch song' (this is the first step of 'Toolbox 1' in the attached figure). After this step we have detected songs as .wav and timestamps.

After the detection step outlined above, we want to identify these annotated song fragments to the individual level using a custom deep learning approach using both the waveform (sound) characteristics and spectrogram characteristics (these are sound visualisations that allow for classifying using computer vision approaches, which are currently much more advanced than sound approaches). We are in the process of developing this pipeline. This is not straightforward as current algorithms typically assign sounds to a finite number of known classes, whereas we will be dealing with both known and unknown individuals/classes. Whether it will be possible to fully automate this, e.g. by using an additional 'not-yet-known' class or whether this will remain dependent on a limited level of manual labour is something we are currently still investigating (this is the second step of 'Toolbox 1' in Figure 1). After this step we have detected individuals and timestamps, which allows for the construction of ecologically relevant information, i.e. social networks of free-living zebra finches (see Figure 1 for Toolbox 2 and beyond which we will not discuss here).

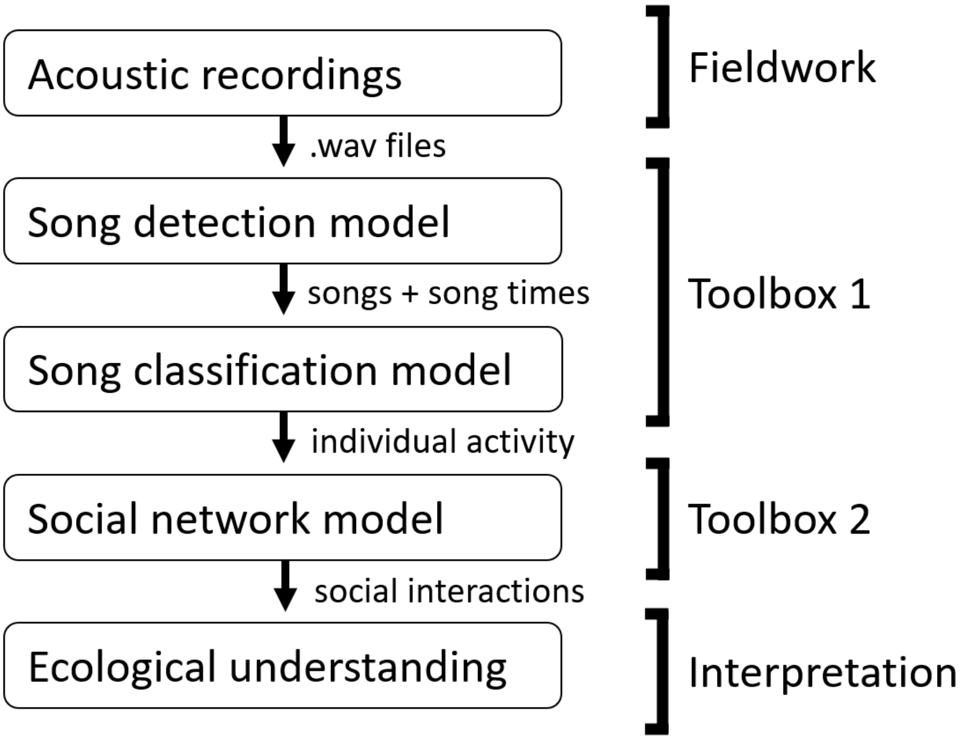

Figure 1. Workflow going from acoustic recordings to ecological understanding

Locations of scripts

The detection algorithm is using BirdNET, which was not developed by us, but can be found here: https://github.com/kahst/BirdNET-Analyzer.

The Github repository with our identification software is coming at a later point.

Lessons learned

- There is a vast array of tools available for the detection of biological sounds in audio streams. The advantage is that there is likely something out there that can do what we as researchers want to do, and we don't need to start from scratch. The big disadvantage is that it requires a large effort to understand which tools are most suitable for a researchers' particular use case, especially for those trained in a different field such as ecology.
- Related to the above point, it is therefore very helpful to work together with machine learning experts to understand better what these models are doing and for selecting the right tool for the job. These collaborations are very valuable.
- It is great that we have so many of that expertise here at WUR. I met my invaluable collaborator at a more-or-less random symposium. Attending talks on topics that are (far) beyond your area of expertise can spark unusual collaborations.
- Computers cannot replace experts; there is not a perfect technical solution for everything. Crucial parts of our pipeline, such as the training data set that we collected and annotated, would have been impossible without the biological training and field experience of our team (including students).

List of people involved and their role

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Output

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