The Automation of Camera Trap Distance Sampling with Machine Learning for the Estimation of Population Density and Abundance

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Abstract

[Abstract]

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Author’s declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University’s Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate’s own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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1 Introduction

Manual distance sampling bottleneck

Aim to automate distance sampling of a large dataset and use estimated distances to achieve accurate estimates for population activity

WCF dataset

How abundance and density is calculated using distances

2 Background

2.1 WCF Dataset

2.2 Methods and Models

2.2.1 Deep Learning

2.2.2 Mega Detector

2.2.3 Segment Anything

2.2.4 Depth Anything

2.2.5 Dense Prediction Transformers

2.2.6 Calibrating Distances

2.3 Estimating Activity

Distance estimation[1]

3 Experimantal

3.1 Calibration Frame Preparation

For each camera location of the dataset, a set of calibration frames (generally fifteen, location dependant) and corresponding binary masks were prepared. The frames were extracted from location-specific reference videos supplied with the dataset consisting of a person standing, facing the camera, at known distance intervals and holding a sheet of A4 paper labelled with the corresponding distance.

3.1.1 Frame Extraction

In an effort to streamline the frame extraction process, an extractor program was created (Figure 3.1). This tool enabled reference videos to be dragged and dropped into a GUI window allowing for the easy navigation between individual frames to extract the optimal one for each distance. With this software, the next/previous frames are accessed with the 'left'/'right' arrow keys, the frame index position is moved ahead/behind 20 places with the 'd'/'a' keys and the frame found at a specific timestamp is accessed with the 's' key followed by entering a time (in seconds) into an input bar. The active frame (at the current index) can be saved to disk with the 'enter' key followed by entering a filename in an input bar.

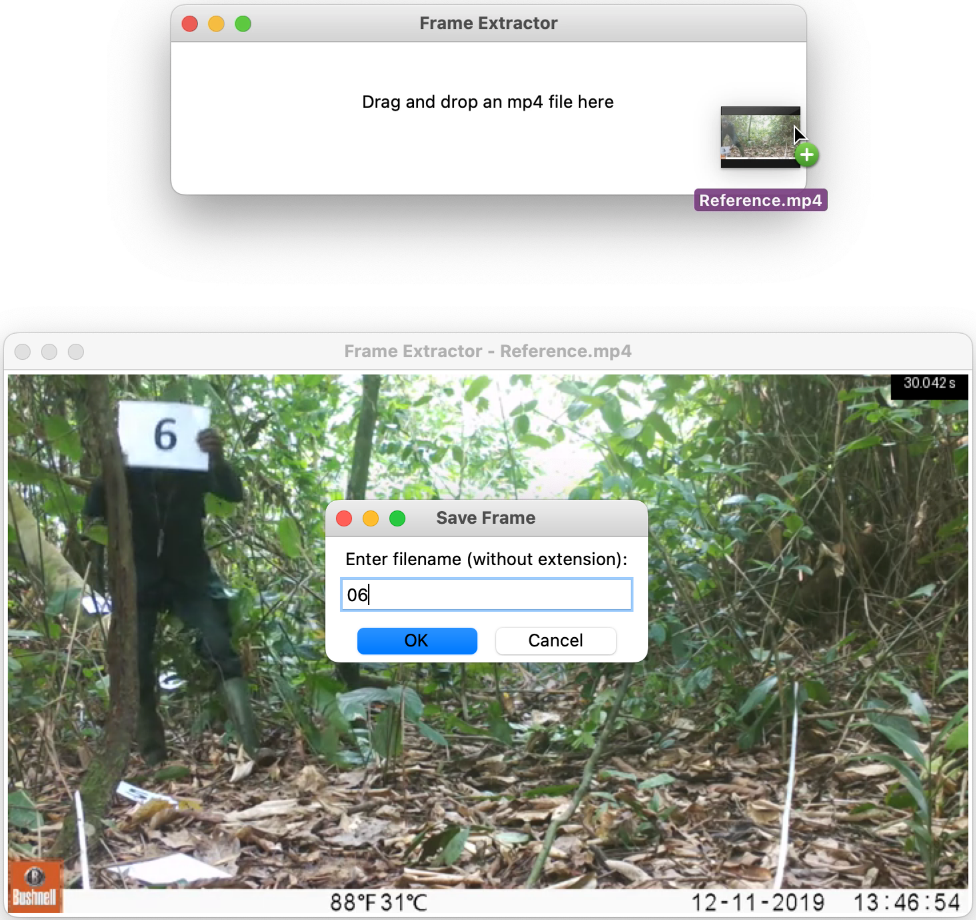

Figure 3.1: Frame extractor program showing the drag/drop (top) and save frame (bottom) features

3.1.2 Frame Mask Creation

For each of the extracted calibration frames, a corresponding binary mask was created. This task can be completed manually using image manipulation software (e.g. Photoshop, GIMP, etc...) where the segmentation boundary is manually traced then filled. This approach, however, is rather labour-intensive, constituting somewhat of a bottleneck, and therefore it is desirable to automate the process.

To assess the feasibility of automation, a two-stage detection/segmentation pipeline was created. Here, raw calibration frames are first processed with YOLOv5 detector[2] to generate bounding boxes enclosing the frame landmarks. The bounding boxes are then passed to Segment Anything Model which predicts segmentation masks for the landmarks.

Two examples of the raw calibration frames (Figure 3.2) along with their corresponding manual (Figure 3.3) and automated (Figure 3.4) masks are shown below.

Figure 3.2: Raw calibration frames

Figure 3.3: Manual calibration frame masks

Figure 3.4: Automated calibration frame masks

3.2 Detection Frame Preparation

Detection frame preparation is the process whereby the raw camera trap video of the dataset is transformed into an array of representative images depicting the chimpanzees whose distances to the camera will be estimated. Two distinct frame sampling techniques were used in this study which will be referred to as 'manual' and 'automated' sampling.

3.2.1 Sampling

2.2.1.1 Manual Sample

Accompanying the raw camera trap video, another component of the dataset is a list of human-annotated distance-to-camera estimates for all observed chimpanzees at a recorded date and time (along with additional metadata). These distance data must be used a benchmark by which the accuracy of any modelled estimates are assessed and therefore the specific frames corresponding to these manual annotations must be sampled.

Before sampling, these data were first cleaned by running an automated script to flag any identifiable abnormalities in the data such as duplicate entries and inconsistencies in the date/time formatting. These were then manually corrected.

In order to identify the correct frames to extract, each of the manual annotations was assigned a timestamp corresponding to a time in seconds in which it was recorded in its associated camera trap video. These timestamps then constituted discreet identifiers of sampled frames.

Although the start-date/times of the videos themselves were not explicitly pre-labelled within the dataset, assigning timestamps was still possible since the date/time at zero seconds into a given video can be inferred as equal to that of the earliest of all recorded annotations associated with the video. This was a valid assumption to make as the overwhelming majority of videos begin exactly at the point in which a chimpanzee enters the frame, thus corresponding to the first annotated observation. In the few rare cases where this heuristic did not apply, all relevant timestamps were manually corrected upon being flagged.

2.2.1.2 Automated Sample

The automated sampling process is significantly more straightforward. Here, detection frames are sampled at an interval of two seconds over all camera trap video in the dataset. Resultant model-estimated distances from this sample are intended to be used purely as distance data for the automated modelling of population abundance.

In contrast to the manual sample, this automated sample is not directly associated with any human-annotated distance estimates. It does, however, remain representative of the dataset, capturing images of the same individual chimpanzees over the same time period. This sample also differs due to the sampling of many 'empty' frames where the image captures no individual. The impact of these empty frames on subsequent abundance estimates will be minimal. The empty frames may collectively incur a small number of false positive detections; however, the total will be negligible and the probability of a given empty frame resulting in a false positive detection is no more likely than that of any other frame.

All in all, this approach exemplifies a simple frame sampling method that can be used as part of an automated distance sampling pipeline.

3.2.2 Frame Extraction

The identified sample frames were extracted from the raw camera trap video using an automated script. Examples of extracted detection frames capturing chimpanzees (Figure 3.5) as well as empty detection frames (Figure 3.6) are shown below.

Figure 3.5: Mixed subsample of extracted detection frames capturing chimpanzees (taken from both the manual and automated sample)

Figure 3.6: Mixed subsample of empty detection frame
(taken exclusively from the automated sample)

3.3 Distance Estimation

DPT/BBOX, DPT/SAM, DA/BBOX, DA/SAM

Code adjustments for blue crystal

Variable calibration runs

Depth map diagrams

3.4 Activity Estimation

Refining activity script based on distribution of estimated distances?

4 Analysis

Analysis of automated calibration frames, overlays, failure cases, etc

4.1 Analysis of Distance Estimates

4.1.1 Model / Manual Distance Comparison

4.1.2 Error Analysis

4.1.3 Qualitative Analysis

close/far failure cases, sweet spot

4.1.4 Effects of Varying Calibration

4.2 Analysis of Activity Estimates

4.2.1 Manual Sample Activity Analysis

Single chimp frame distances supplemented with manual distances

4.2.2 Automated Sample Activity Analysis

5 Evaluation of Methodology

Improvement over fully manual approach?

Bottlenecks, calibration frame preparation, available compute

Time saved using frame extractor, preserves exact pixels

Limitations of the environment

Calibration and detection frame image resolution

Depth estimation point consistency (the animal itself has depth)

Error in reference videos (person has depth, not always standing up straight)

Better calibration (polynomial/not just linear, more calibration frames)

6 Conclusion

6.1 Further Work

References

[1] T. Haucke, H. S. Kühl, J. Hoyer, and V. Steinhage, "Overcoming the distance estimation bottleneck in estimating animal abundance with camera traps," *Ecological Informatics*, vol. 68, p. 101536, 2022. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1574954121003277

[2] R. Khanam and M. Hussain, "What is yolov5: A deep look into the internal features of the popular object detector," 07 2024.