The Great Grevy's Rally: A Review on Procedure

Jason Parham
Charles Stewart
Rensselaer Polytechnic Institute
Troy, New York 12180

Tanya Berger-Wolf
University of Illinois, Chicago
Chicago, Illinois 60607

Daniel Rubenstein
Princeton University
Princeton, New Jersey 08544

Jason Holmberg
Wild Me, Non-profit
Portland, Oregon 97217

Abstract

A single census of an animal population is critical in monitoring its health, determining its endangerment status. Repeat censuses, however, that can track individuals through time can unveil ecological data that is not normally available from classical counting-based techniques. We review the procedure of the Great Grevy's Rally from January 2016 and its ongoing repeat census, the Great Grevy's Rally performed in January 2018, to provide an overview of our citizen science data collection process and the computer vision processing pipeline.

Introduction

A census is critical in monitoring the health of an animal population because it allows for the analysis of the individual across time. Ecological metrics like life expectancy, individual migration behavior and social relationships are beyond the current ability of a simple counting-based estimate [Chase *et al.*, 2016; Swanson *et al.*, 2015] that does not track the resighting of known animals. Furthermore, the large logistical demands of performing an comprehensive individual census can be overcome by 1) using citizen scientists [Cohn, 2008] to rapidly collect a large number of photographs and 2) using computer vision algorithms to process these photographs.[1]

While a single population census can provide an accurate estimate of the population, it is only a single snapshot in time and, therefore, only provides limited temporal ecological data. We present in this paper the preliminary collection statistics of the Great Grevy's Rally 2018 (GGR-18) held January 27-28, 2018 in a region of central and northern Kenya covering the known migratory range of the endangered Grevy's zebra (*Equus grevyi*) and Reticulated giraffes (*Giraffa reticulata*). The GGR-18 was specifically sanctioned as a reproduced census of the Great Grevy's Rally 2016 (GGR-16) [Parham *et al.*, 2017] as to provide a current population estimate and collect resightings of individuals across a two-year time span. The Great Grevy's Rallies use an updated and field-tested protocol for decentralized data collection first proposed in [Parham, 2015] and we review the procedure used during these events.

[1]Portions of this paper were presented in [Parham *et al.*, 2017]

	Cars	Cameras	Photographs
GGR-16	121	162	40,810
GGR-18	143	214	49,526

Table 1: The number of cars, participating cameras (citizen scientists), and photographs collected between the GGR-16 and the GGR-18.

Procedure

Our censusing rallies are structured around the traditional protocols of mark-recapture [Chapman and Chapman, 1975; Pradel, 1996] and its sight-resight variant [Hiby *et al.*, 2013]. We refer the reader to [Parham *et al.*, 2017] for a discussion on the statistics of population estimates, the biases inherent in a citizen scientist-based data collection, and high-level details of the computer vision pipeline used during processing.

Collection of Imagery

A key feature of the censusing procedure is the ability to decentralize, and therefore inherently parallelize, the collection of the animal imagery. In fact, the robustness of the sight-resight study is critically dependent on capturing as many sightings and resightings of individuals as possible as our system relies on duplicate sightings. This is in sharp contrast to a count-based estimate which must always be mindful of double counting and overlapping sample regions. The further advantages of using cameras during a census is that it 1) provides actionable evidence of where a specific individual was in time and location (which allows for the possibility of future auditing) and 2) the mechanism is easy to teach to the average person. By not requiring specialized hardware – only a car and a GPS-enabled camera – a large area can be surveyed in

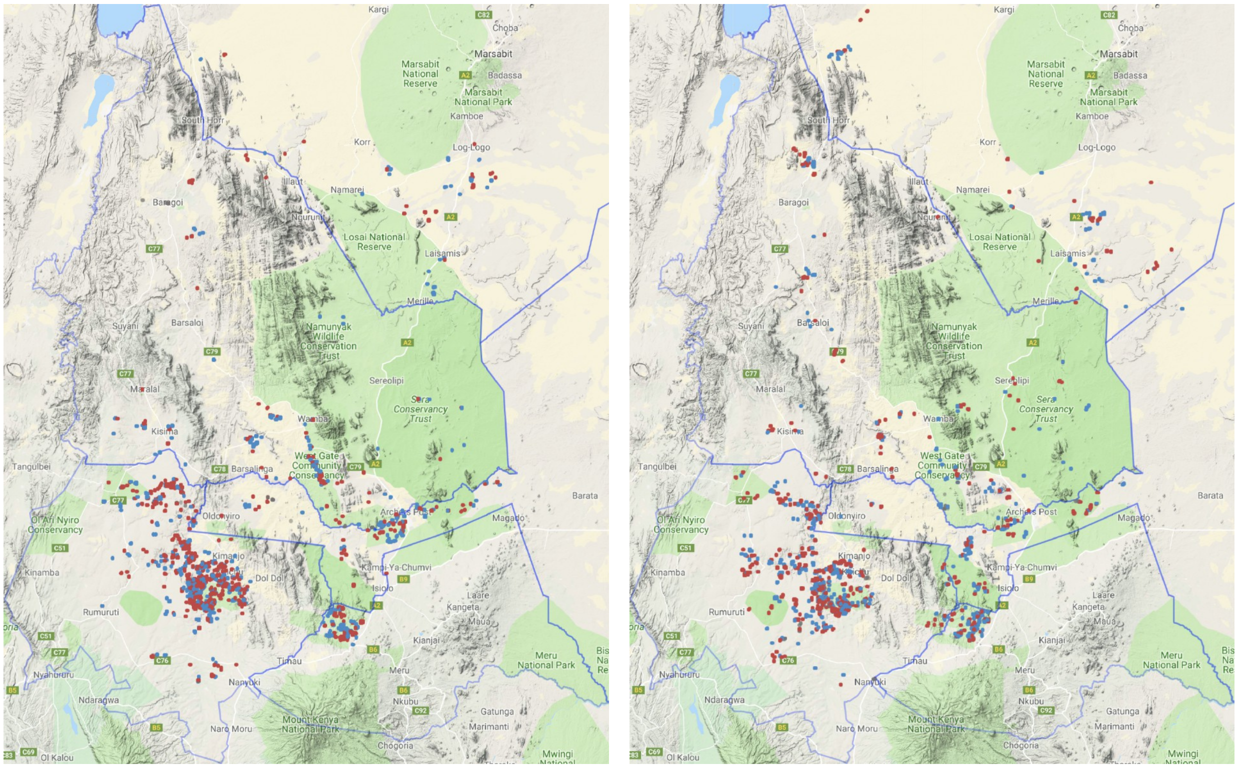

Figure 1: The locations of photographs taken during the GGR-16 (left) and the GGR-18 (right). Red indicates images from day 1, blue from day 2 of each event, respectively. The blue area lines indicate Kenyan county boundaries. Rendered with Google Maps. Best viewed in color.

an efficient manner with many photographers overlapping the same geographical area and at concurrent times.

After a brief training procedure, the photographers are asked to go into a survey area by car and capture images of the species of interest (i.e. Grevy's zebra and Reticulated giraffe). The number of cars, volunteers, and the number of photographs taken for both rallies can be seen in Table 1. It is worth noting that the number of images collected during the GGR-18 is 20% higher with 30% more photographers. Another feature of the data collection is it's cost effectiveness, where citizen scientists, volunteers, tourists, field guides, school children, park rangers, scientists, and any other stationary ground-based sources (e.g. camera traps) can all equally contribute useful data. In our experience with the GGR-16 and GGR-18, the intrinsic worth of being a member of a scientific endeavor tends to be compensation enough for participating individuals, also making it a very effective method of community engagement. Refer to [Parham, 2015] for how to reward participants with same-day feedback on their contributions, which they have freely given their time and imagery towards the censusing event.

Once the imagery is collected and aggregated by census staff, the imagery is ingested into a web-scale platform[2] for further processing.

[2] Wildbook, http://www.wildbook.org

Curation of Detections

We begin the processing of the imagery by localizing and classifying the sightings found within the collected images. The reason this curation stage is critical for identification is multi-faceted, where the detection processing pipeline should:

- filter out irrelevant images by determining the list species within the image,
- localize bounding boxes around all animals,
- classify each bounding box with a species and viewpoint (e.g. left, right, top, back-left, etc),
- segment a coarse foreground-background mask, and
- classify each bounding box as being "identifiable"

These 5 steps were previously presented in [Parham *et al.*, 2018] with the release of a new curated dataset called `WILD`, containing 5,784 images, 9,871 bounding boxes, and 6 species in the PASCAL VOC format.

To train these 5 components, the collected imagery data must be manually reviewed to annotate axis-aligned bounding boxes with identifiable flags, species, and viewpoint metadata on each. For the GGR-18 we manually reviewed 10% of all collected images with 3 reviewers per image during the bounding box annotation step. The user inputs are aggregated per image into a single list of bounding boxes and are classified by a reviewer to specify species and viewpoint. An important point is to curate bounding boxes and metadata for all animals in the image, not just for the species of interest. This distinction is important for training deep learning detection models that rely on saliency-style bounding box proposals that may not distinguish between visually similar species (sub-species of zebra, for example).

The human curated data is used to train computer vision algorithms to perform these tasks automatically and are applied to the remaining 90% of the training data with configuration parameters specified using a validation set that was held-out from the reviewed 10%.

Curation of Identifications

The bounding boxes with the correct species and viewpoint are selected for identification. For the GGR-16 and GGR-18, we filtered the viewpoint to only the `right` side (+/- 45 degrees) of the animals and only the species of interest. A matching algorithm uses the foreground-background segmentations to weight and correspond automatically extracted key-points and a ranking algorithm to aggregate and order the matches for review. A novel random-forest verifier and a graph-based algorithm [Crall, 2017] are then used to automate match decision, prioritize which matches need to be manually reviewed, and resolve any inconsistencies within the set of named individuals. Refer to [Parham *et al.*, 2017] for more detail.

After the final set of named individuals has converged, ecological experts are asked to manually annotate age and sex information. For a given individual, the reviewer is presented with all of its sightings in a web interface to allow for a more accurate decision across all images. The turking of age and sex also allows for last method of error checking, where any cross-gender or cross-age matching mistakes can be noticed and corrected. Another name-based matching check is to ensure travel constraints through GPS and time EXIF metadata; for example, any animal that is found to have travelled too far or in too short of a time span is marked as a potential incorrect identification and sent for additional review.

The end result is a final list of the named animals with age and sex information, which would then be compared to any previous years to develop a list of deaths, births, migration patterns, and other ecological data.

Conclusion

Our procedure encompasses the entire process from start to finish of a photographic census: from the engagement of citizen scientists for decentralized image collection, to the parallel annotation of new training data, to the training and inference of automated decision making with computer vision algorithms, to the final population estimates with their valuable individual ecological, social, and temporal data. The procedure has been shown to be viable at scale and produce numbers that are consistent with previously known estimates for the population in the Nairobi National Park [Ogutu *et al.*, 2013] and for Grevy's Zebra in Kenya [Ngene *et al.*, 2013].

Our future work will be in completing the analysis of the GGR-18 data, presenting the 2018 population estimates for Grevy's zebra and Reticulated giraffes, and comparing the resighted individuals against the established population baseline from the GGR-16.

References

[Chapman and Chapman, 1975] Donald Chapman and Norma Chapman. *Fallow deer: their history, distribution, and biology*. Dalton, 1975.

[Chase *et al.*, 2016] Michael J. Chase, Scott Schlossberg, Curtice R. Griffin, Philippe J.C. Bouch, Sintayehu W. Djene, Paul W. Elkan, Sam Ferreira, Falk Grossman, Edward Mtarima Kohi, Kelly Landen, Patrick Omondi, Alexis Peltier, S.A. Jeanetta Selier, and Robert Sutcliffe. Continent-wide survey reveals massive decline in african savannah elephants. *PeerJ*, 4(1):e2354, 2016.

[Cohn, 2008] Jeffrey P. Cohn. Citizen science: Can volunteers do real research? *BioScience*, 58(3):192–197, 2008.

[Crall, 2017] Jonathan P. Crall. *Identifying Individual Animals using Ranking, Verification, and Connectivity*. Ph.d. dissertation, Department of Computer Science, RPI, 2017.

[Hiby *et al.*, 2013] Lex Hiby, William D. Paterson, Paula Redman, John Watkins, Sean D. Twiss, and Patrick Pomeroy. Analysis of photo-id data allowing for missed matches and individuals identified from opposite sides. *Methods in Ecology and Evolution*, 4(3):252–259, 2013.

[Ngene *et al.*, 2013] Shadrack Ngene, Joseph Mukeka, Festus Ihwagi, James Mathenge, Anthony Wandera, George Anyona, Nyumba Tobias, Lidemta Kawira, Irene Muthuku, Joseph Kathiwa, and others. Total aerial count of elephants, grevyszebra and other large mammals in laikipia-samburu-marsabit ecosystem in (november 2012). Technical report, Kenya Wildlife Service, 2013.

[Ogutu *et al.*, 2013] Joseph O Ogutu, Norman Owen-Smith, Hans-Peter Piepho, Mohammed Y Said, Shem C Kifugo, Robin S Reid, Helen Gichohi, Paula Kahumbu, and Samule Andanje. Changing wildlife populations in nairobi national park and adjoining athi-kaputiei plains: collapse of the migratory wildebeest. *Open Conservation Biology Journal*, 7(1):11–26, 2013.

[Parham *et al.*, 2017] Jason Parham, Jonathan Crall, Charles Stewart, Tanya Berger-Wolf, and Daniel Rubenstein. Animal population censusing at scale with citizen science and photographic identification. In *AAAI 2017 Spring Symposium on AISOC*, 2017.

[Parham *et al.*, 2018] Jason Parham, Jonathan Crall, Daniel Rubenstein, Jason Holmberg, Tanya Berger-Wolf, and Charles Stewart. An animal detection pipeline for identification. In *2016 IEEE WACV-W*, pages 1–9, 2018.

[Parham, 2015] Jason R. Parham. Photographic censusing of zebra and giraffe in the nairobi national park. M.s. thesis, Department of Computer Science, RPI, 2015.

[Pradel, 1996] R. Pradel. Utilization of capture-mark-recapture for the study of recruitment and population growth rate. *Biometrics*, 52(2):703–709, 1996.

[Swanson *et al.*, 2015] Alexandra Swanson, Margaret Kosmala, Chris Lintott, Robert Simpson, Arfon Smith, and Craig Packer. Snapshot serengeti, high-frequency annotated camera trap images of 40 mammalian species in an african savanna. *Scientific Data*, 2(150026):1–14, 2015.