Developing a Citizen Science Web Portal for Manual and Automated Ecological Image Detection

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Wildlife@Home

http://csgrid.org/csg/wildlife/

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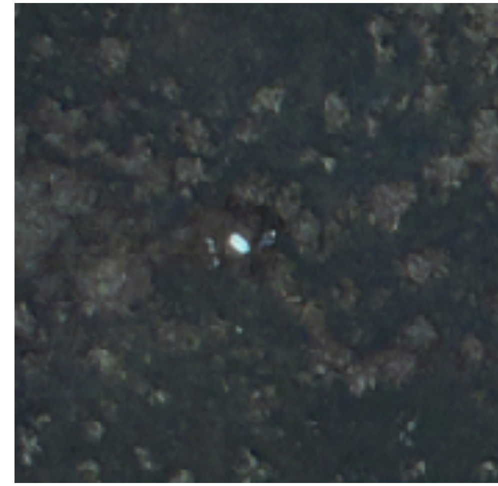
What is Wildlife@Home

- A *citizen science* project that combines both crowd sourcing and volunteer computing
- Users volunteer their brain power by observing videos and images and reporting observations
- Users volunteer their computing power by downloading videos and performing computer vision computations
- A scientific web portal to robustly analyze and compare results from users, experts, and the computer vision techniques

Images collected for research

- All imagery used for this research is from the Hudson Bay area of Manitoba, Canada
- Trail cameras deployed to learn about predators destroying nests
  - Common eider and lesser snow geese
  - 85 cameras
  - 100 nests
  - Primary issues:
    - Cryptic coloration (camouflage), obscuring vegetation
- Unmanned Aerial System (UAS) imagery flown along predetermined transects
  - Lesser snow geese
  - Vegetation and other landmarks
  - **Focus of this research**
  - Primary issues:
    - Cryptic coloration of the blue phase lesser snow geese
    - Small objects in comparison to the images





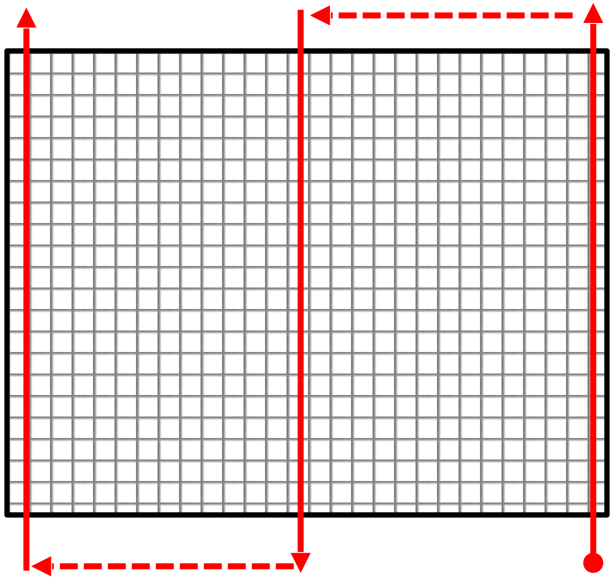
How many Lesser Snow Geese are in these images? **2 in each!**



Changing lighting conditions add to the difficulty of image processing.

UAS Image Collection

- In summer 2015, a Trimble UX5 fixed wing UAS was flown at Wapusk National Park in Manitoba, Canada
- Flights were flown at 75m, 100m, and 125m on pre-defined transects with 80% overlap
- Images were taken with a 16 megapixel Sony red, green, blue camera in the Nadir position



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UAS Dataset

- 60,000 images were produced from the flights
- 10 mosaics were created using Trimble
- Over 1 Terabyte of image data, with more data being generated each year
- Too much data for experts to analyze alone!
- That's where *citizen scientist* come in

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Creating a UI for Image Observations

- Web-based user interface with touch capabilities for tablets and desktops
- Present the same image to three (or more) users
- Match user observations of a single object
- Extract observed objects from images

Challenges with creating the UI

- Images can be significantly larger than the typical viewport of a desktop monitor, e.g. 1920x1080 pixels
- Observed objects that are too small (only a few pixels square) do not make good candidates for computer vision techniques
- The interface must be usable across a variety of viewports, operating systems, and input devices
- The UI must be usable and extensible for multiple projects and image sources
  - Specifically, the trail cams and UAS imagery

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Overcoming large images

- Large images are split into either 25 or 100 smaller images, depending on the size
- Resultant images are constrained to approximately 1280 pixels
  - The splitting of images is being re-written to force this maximum constraint
- Use an HTML5 Canvas to allow the user to scroll in any direction and zoom the image, in the case that the image is still larger than the viewport
  - This is especially useful on tablets

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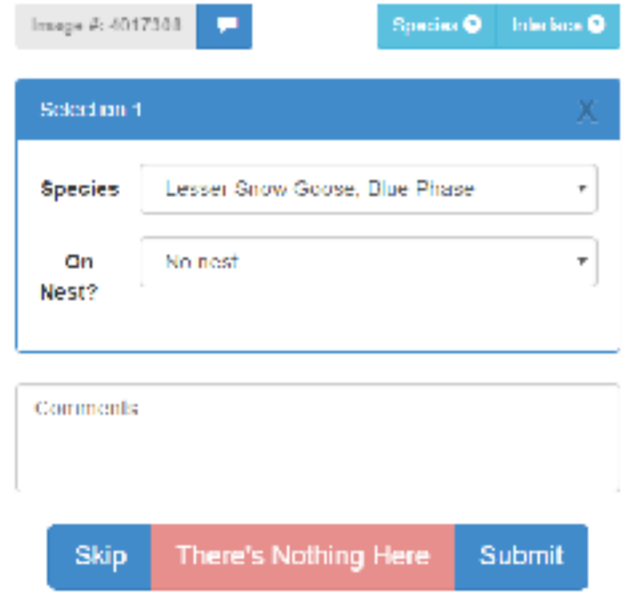
- HTML5 Canvas Element
  - zoomable (scroll-wheel or pinch)
  - pannable (click-drag or touch-drag)
- Zoom level
  - current magnification level
- Scroll location (X and Y)
  - shows the current location and size of the image shown
  - relative to the true size of the image

Enforcing a minimum size limitation

- Bounding boxes are created by double-tapping the image to signify an object observation
  - User then identifies the species
  - Resizable and movable
- Objects that are too small do not contain enough data to provide good computer vision training
- Observations are therefore limited to a minimum 5-pixel with and height (25-pixels square)



Observation classification

Corresponding bounding box in the interface

Usability on a variety of hardware

- HTML5 and JavaScript are the only languages required to run the UI
  - Modern browsers, including phone and tablet browsers, are compatible with both technologies
  - Usable on Android, iOS, Windows, Linux, Mac, etc.
- Hammer.JS is used to provide touch-capable inputs to the HTML5 Canvas element

Ensuring good observations

- Computer vision techniques require the positive samples (observations) to have a low background-to-object ratio
  - If there is too much background information, the object may be incorrectly identified in the background of images
- Different users provide different bounding boxes with varying degrees of background information for the same objects

Mapping observations

- Use multiple observations to determine a "true" observation
  - Trust multiple users, not just a single user
- Match user observations of the same object
  - Only accept objects which have observations from multiple users
  - Two (2) algorithms tested
- Determine the "true" bounding box for the matched objects
  - Two (2) algorithms tested with multiple parameters

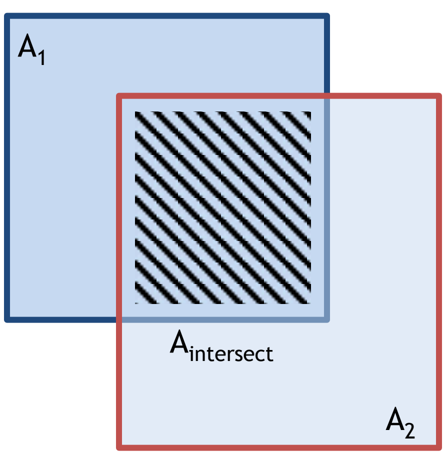
Matching algorithms

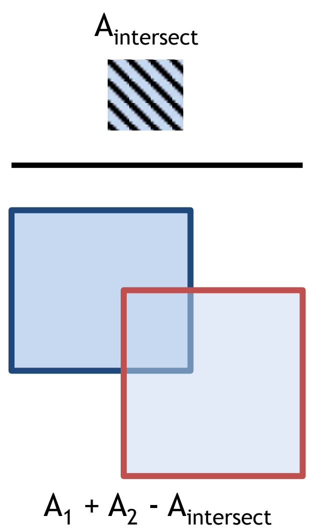
1. Area Overlap
   - Compares the total amount of area of the overlap between two observations
   - Returns the overlapping area as a percentage relative to the total area of the observations
2. Corner-point Distance
   - Calculates the maximum distance between the four corners of two observations
   - Returns the maximum distance calculated

Matching algorithms, cont.

Area Overlap

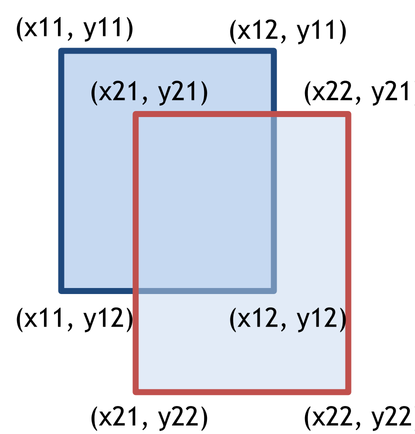
$$
\begin{aligned}
l_{intersect} &= \min\|x_{12}, x_{22}\| - \min\|x_{11}, x_{21}\| \\
h_{intersect} &= \min\|y_{12}, y_{22}\| - \min\|y_{11}, y_{21}\| \\
A_{intersect} &= \max\|0, l_{intersect} * h_{intersect}\| \\
A_{union} &= A_1 + A_2 - A_{intersect} \\
A_{overlap} &= \frac{A_{intersect}}{A_{union}}
\end{aligned}
$$

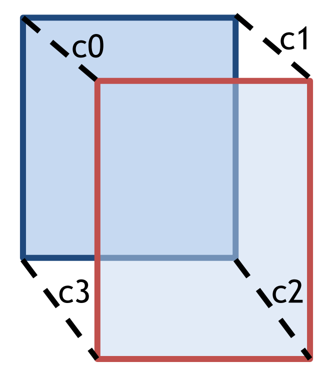




Corner-Point

$$
\begin{aligned}
c_0 &= \sqrt{(x_{11} - x_{21})^2 + (y_{11} + y_{21})^2} \\
c_1 &= \sqrt{(x_{12} - x_{22})^2 + (y_{11} + y_{21})^2} \\
c_2 &= \sqrt{(x_{12} - x_{22})^2 + (y_{12} + y_{22})^2} \\
c_3 &= \sqrt{(x_{11} - x_{21})^2 + (y_{12} + y_{22})^2} \\
c_{max} &= \max\|c_0, c_1, c_2, c_3\|
\end{aligned}
$$





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Matching algorithm results

Algorithm	Matches	Non-Matched	False Positives	False Negatives
Actual	400	91	0	0
Area (50%)	352	122	0	54
Area (60%)	329	159	0	92
Area (70%)	266	282	0	214
Area (80%)	186	440	0	370
Area (90%)	81	649	0	566
Point (5px)	238	341	0	272
Point (10px)	379	106	0	24
Point (15px)	404	91	8	0
Point (20px)	414	91	18	0

MATCHES OF THE 811 OBSERVATIONS FROM 142 IMAGES IN THE TEST DATASET

- **Matches** is the number of matched observation pairs
- **Non-Matched** is the number observations without a matched pair
- **False positives** are matches that are not actual matches
- **False negatives** are when the algorithm fails to match observations that should match

- **Point (10px)** is chosen as the matching algorithm because:
  - provides the highest matched ratio (0.95)
  - provides a low non-matched ratio (1.16)
  - has no false positives and few false negatives

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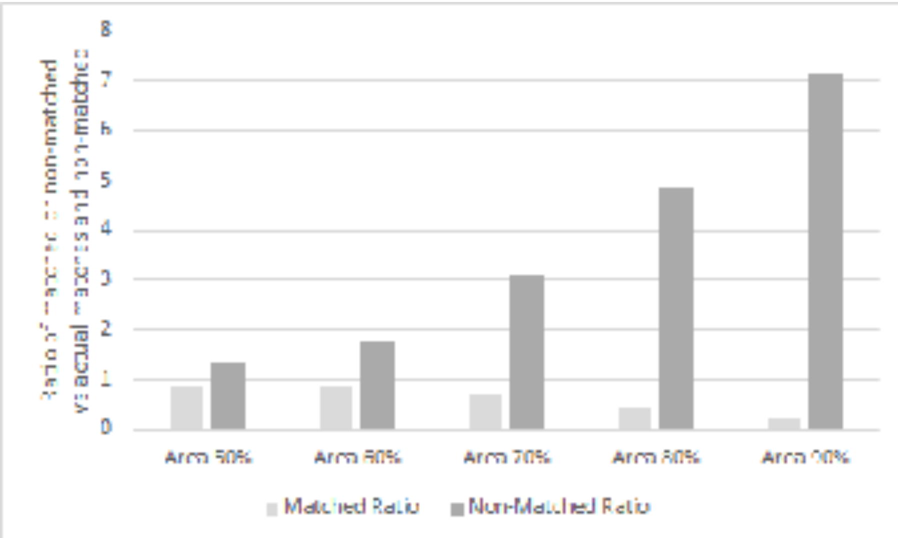
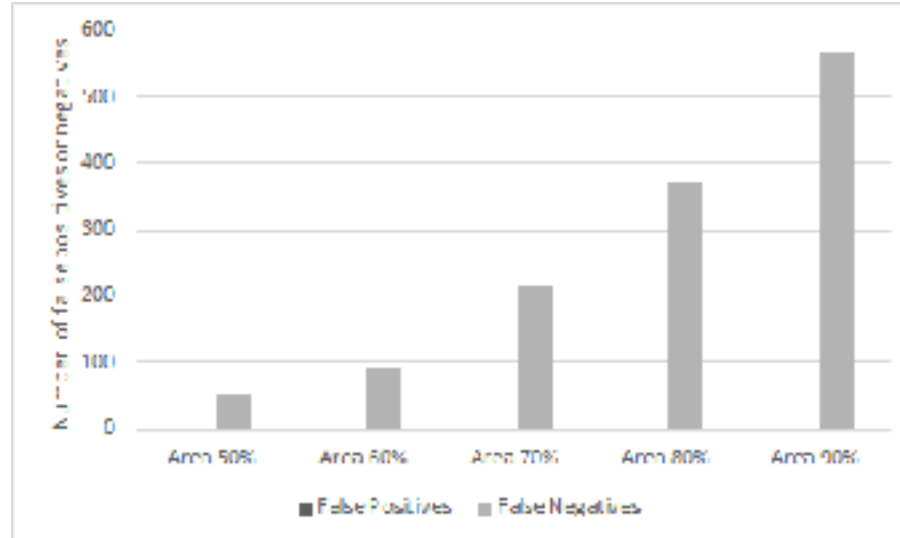
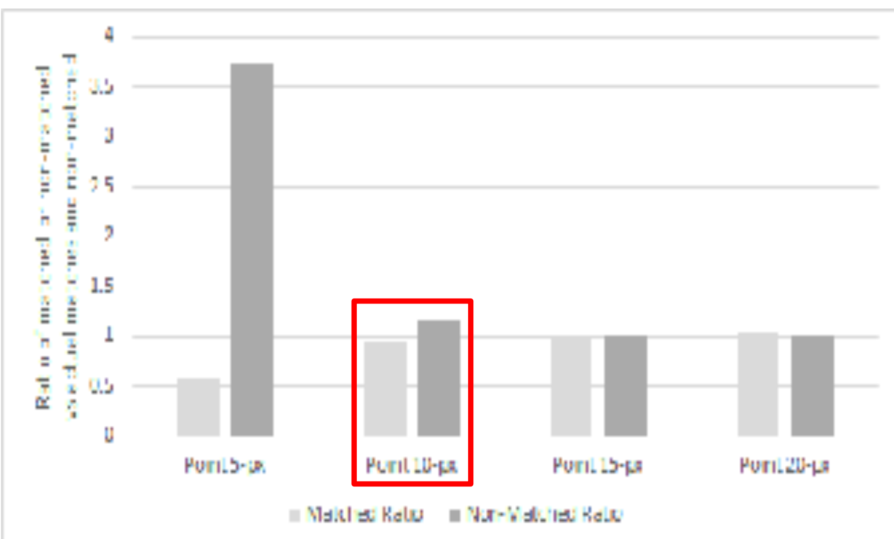
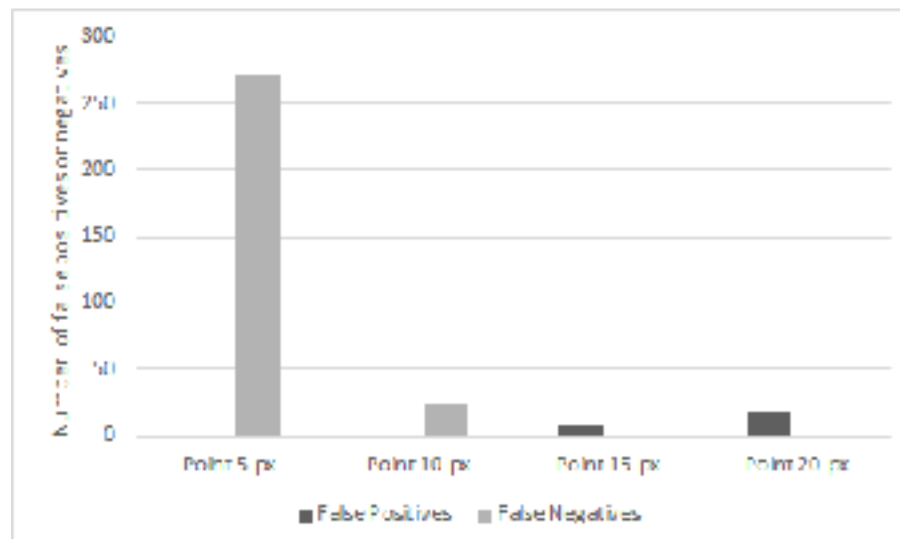
Matches vs Non-Matches

False Positives and Negatives









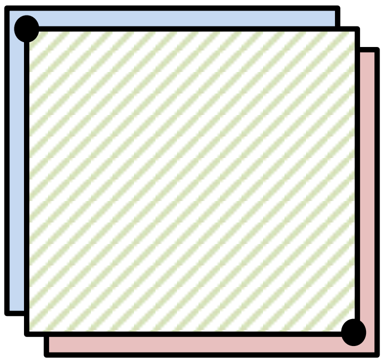
Observation extraction

- Now that we have a set of matched observation, we have to use the aggregate bounds to create the “true” bounds

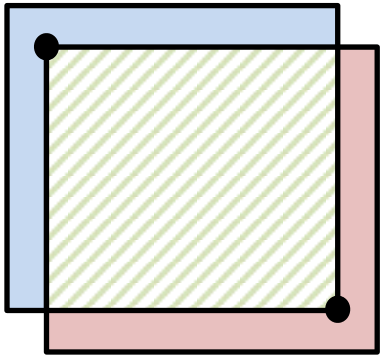
1. Average extraction method
   - Averages the location of each corner
   - EASY TO SKEW WITH **TOO MUCH BACKGROUND**
     - All inputs have the same weight
     - Relies on all users to give relatively good input
2. Intersection extraction method
   - Pulls out the intersection of each observation
   - EASY TO SKEW WITH **TOO LITTLE POSITIVE DATA**
     - Relies on a single user having good input
     - Minimizes background noise
     - A single box too small can give less positive data than is present

Observation extraction, cont.

Average



Intersection



Observation extraction results

- Difficult to analyze the amount of negative space programmatically
- Initial manual inspection shows that the **intersection method** is significantly better than the average method

Conclusions

- Citizen scientists do a good job finding objects
  - only 11.2% of observations failed to be matched with an observation from another user
- However, there is relatively high variability in the bounding boxes around the objects
  - Fatigue, human error, speed, lack of training, etc.
- Using the Corner-Point matching algorithm with a 10-pixel parameter and the Intersection extraction method provide the best positive data set

Future Work

- Compare the results of citizen scientist with those of trained experts
  - show that citizen scientists produce observations similar to the experts
- Train a neural network using the objects extracted from the citizen scientist observations
  - initial work has begun using OpenCV
  - more citizen scientist observations required to build the positive dataset

Acknowledgements

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QUESTIONS?