Automated Aerial Estimation of Floating Trash Density Using Computer Vision Techniques

Ethan Cheung
ethan.cheung27@bcp.org

1. Introduction

1.1 Background

Waterborne trash is an environmental concern not only because of its impact on ecosystems, but also because it is often concentrated in specific areas rather than evenly distributed across the water surface. Without reliable information about where trash is most concentrated, cleanup efforts within lakes become inefficient and difficult to prioritize.

At present, estimating the density and location of waterborne trash usually relies on manual visual inspection at multiple sites. Cleanup prioritization is therefore based on limited, localized observations, and because floating trash can shift over time, hotspot locations may change, making it challenging to consistently monitor high-density areas.

1.2 Problem

This research aims to support volunteers and trash cleanup organizers by helping identify high-impact cleanup areas through automated analysis of aerial-style images. By providing a clearer and more consistent view of trash distribution over time, this approach has the potential to improve cleanup planning and support more effective monitoring of water resources.

2. Investigation

2.1 Methodology

Because of constraints relating to the flight of real drones, this project will focus on creating a mock-up system to prove feasibility. The model of the lake is constructed from a sheet of blue paper measuring 28 by 22 inches, with random assorted Legos scattered across its surface to represent floating trash. On the 4 corners and the middle of the areas between them, I printed out 8 ArUco markers to allow the camera to triangulate its position relative to the blue paper. The corner markers were 2 inches wide and 3 inches tall. The other markers were 3 inches wide and 4 inches tall. They were laid out as shown in Figure 1.

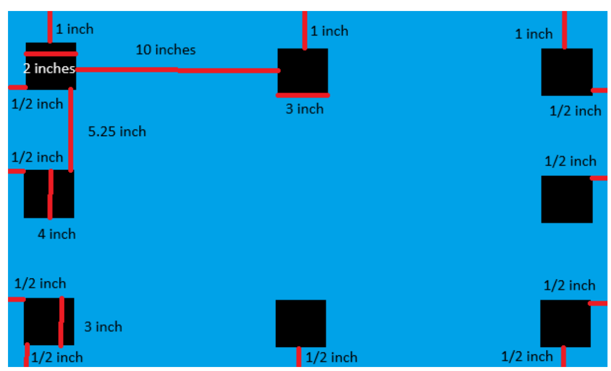

Figure 1. The layout of the ArUco markers. It is important to note that the corner markers are slightly smaller than the other ones and that all the markers are not equidistant from the edge of the paper because they were printed out on small rectangles.

If I were to use a real drone, the drone's position would be instead discovered using an onboard GPS system. To simulate a drone *flying across the water to scan the surface of the lake, I held my phone roughly 3 feet above the sheet of paper and slowly moved it back and forth over the paper, thoroughly scanning it. I made sure to record the entire area of the blue paper and the process took from 30 seconds to a minute to complete. The resulting .MOV video was then sent to the Raspberry Pi for processing.*

The video frames were analyzed one by one. First, the image needed to be aligned using the ArUco markers and homography transformation. Homography is essentially a series of matrix transformations used to map points in two image planes with one another. In this case, it was used to ensure the camera's video was always taken from a consistent top-down view, no matter if the camera was held at a slight angle.

Figure 2. An example setup. The ArUco markers can clearly be seen along the edges of the blue paper and the Lego bricks representing trash sit in the middle.

It was also used to align each frame relative to each other in order to ensure the moving camera wouldn't cause a single cluster of trash to be counted twice because it appeared to have moved when the camera moved. computer vision was used to determine the color of the background by examining the most common color in the image. Any pixels not of that color were designated to be trash. Next, a grid was created over the image. Computer vision was then used to determine where the centers of the trash clusters were, and the grid cells the centers were in were marked as having trash. The more centers were in a cell, the more trash-dense that cell was designated as. After this process is repeated with every image frame, the resulting heatmap is exported as a PNG file, with an overlay option also available to see the heatmap over the trash.

2.2 Results

As a whole, my project was a success. The heatmap was generally aligned to the trash's location, with hotspots appearing over the trash's location. The reproducibility was 100%, meaning when the algorithm was fed the same video, it outputted the same result every time. I met my FPS and latency targets very easily, with the average FPS being 52.78 and the average latency, or the time taken to process one frame, being 18.97 milliseconds.

For hotspot agreement between the heatmap and the trash's actual location, I had to visually compare the two images and rate their similarity. I would look at both the heatmap and the picture of trash position, along with the heatmap overlaid atop the trash picture. I would then estimate how closely each heatmap was. The agreement ranged from 70% to 100%, with the average being 85% agreement, a respectable number.

3. Conclusion

3.1 Related Work

Methods for scanning bodies of water for trash already exist, but they have drawbacks that this project solves. Satellites such as the Copernicus Sentinel-2 can scan large swathes of water at a time, but they can take days to get into the right location to perform a scan.

Drone-based systems like MARLIT can use deep learning to detect floating trash, but it is not a real-time system. Users also need to use R/RStudio, install code, and figure out how to use nadir-position images, presenting a significant barrier to use. In contrast, this project is real-time and cheap and simple to run. It only requires a camera-mounted drone and a Raspberry Pi, and can return an output in minutes.

3.2 Limitations

While conducting this project using a mock-up provided valuable data, it would have been ideal to use a real drone on a real body of water. Furthermore, I would like to use AI in the future. For this project, we found the Hailo AI model wasn't consistent, but I feel it could help reduce the problems shadows, reflections, and non-trash objects might cause.

3.3 Societal Impact

This project would most benefit smaller volunteer groups such as school clubs. Larger organizations could use more effective methods, such as the use of satellites or drone scanning that isn't real-time. However, because my project is real-time and low-cost, smaller groups who still want to clean up waterborne trash can go out with a cheap drone and raspberry pi, find where the trash is, then clean it up, hopefully all in a single day.

4. References and Additional Details

4.1 References

[1]
O. Garcia-Garin et al., "Automatic detection and quantification of floating marine macro-litter in aerial images: Introducing a novel deep learning approach connected to a web application in R," Environmental Pollution, vol. 273, p. 116490, Mar. 2021, doi: https://doi.org/10.1016/j.envpol.2021.116490.
[2]
"Copernicus Sentinel-2 helps advance marine debris detection - Sentinel Success Stories - Sentinel Online," Sentinel Success Stories, Mar. 26, 2020. https://sentinels.copernicus.eu/web/success-stories/-/copernicus-sentinel-2-helps-advance-marine-debris-detection

4.2 Disclosures & Acknowledgements

The Hailo AI module was originally used to try and detect trash clusters. Chat GPT was also used to research homography and Aruco markers.