Searching for Uncollected Litter with Computer Vision

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Abstract

This study combines photo metadata and computer vision to quantify where uncollected litter is present. Images from the Trash Annotations in Context (TACO) dataset were used to teach an algorithm to detect 10 categories of garbage. Although it worked well with smartphone photos, it struggled when trying to process images from vehicle mounted cameras. However, increasing the variety of perspectives and backgrounds in the dataset will help it improve in unfamiliar situations. These data are plotted onto a map which, as accuracy improves, could be used for measuring waste management strategies and quantifying trends.

Introduction

- Waste production is doubling every decade
- Only 10% of plastic is recycled
- 270 species are harmed or killed by waste pollution
- Globally costs over $200 billion a year
- Waste produces 5% of global GHG emissions
- 80% of marine waste originates on land

Research Question

Can computer vision help identify new areas that need to be cleanup and measure how much waste is removed?

Methods

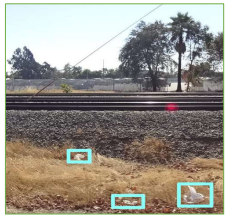
- Algorithm: Masked Regional Convolutional Neural Network
- Training dataset: Trash Annotations in Context
- Detection datasets: Mapillary and hand collected images

Trash Annotations in Context (TACO)

Masked Regional Convolutional Neural Network (Mask R-CNN)

Clean Up

Mapillary



Results

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Mapillary: Precision = 1% and recall = 3%
Clean Up Images: Precision = 81% and recall = 74%

Challenges

- Mask-RCNN can't translate to a new perspective
- Low quality images cause noise
- New backgrounds causing lots of false positives

Future Work

- Increase the size of the TACO dataset
  - Adding images, community annotations, new categories
- Continue training with images from new perspectives
  - New perspectives, backgrounds, and devices
- Fix car mislabeling issue using new training images

Conclusion

- For car mounted camera detection many more images are needed
- Detection works on smart phone images and can be used in clean up strategies today
- References available upon request from julianhernandez@csus.edu