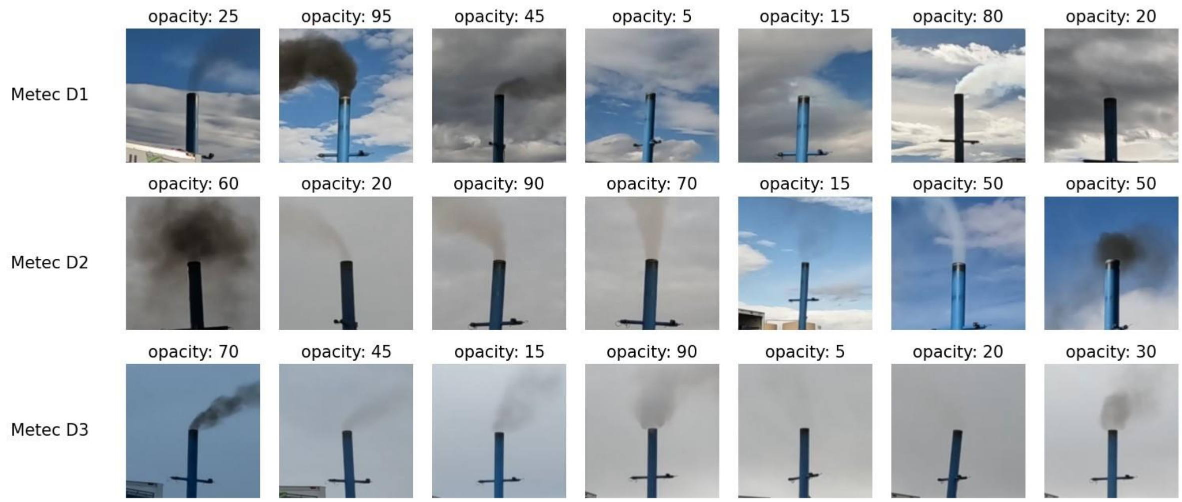
Ethan Seefried, MS Computer Science



Current Project Overview

Computer vision has traditionally faced difficulties when applied to amorphous objects like smoke, owing to their ever-changing shape, texture, and dependence on background conditions. While recent advancements have enabled simple tasks such as smoke presence detection and basic classification (i.e., black or white shade), quantitative opacity estimation in line with the assessments made by certified professionals remains unexplored. To address this gap, we introduce the SMOKE dataset, which features opacity labels verified by three certified experts. Our dataset encompasses five distinct testing days, two data collection sites in different regions, and a total of 13,632 labeled clips. Leveraging this data, we developed a state-of-the-art smoke opacity estimation method that employs unique spatial and temporal modules for robust opacity estimation. We validate the robustness of our model using the SMOKE dataset, achieving state-of-the-art performance under a variety of conditions, locations, and viewing angles.

Research Progress

Multiple parts of the project have been completed, with the overall project in the final stages of being complete. The collection and annotation of the data were completed in Spring of last year, while this semester's focus has been on the implementation of and testing new machine learning models. Key results that have been gathered are listed here:

- Baseline models have been established and trained on the SMOKE dataset. These models include traditional neural networks such as R3D and among others, which are omitted for the sake of future publications along with corresponding results.
- An in-depth comparison of other datasets was conducted. Other datasets that are publicly available typically cover only smoke detection, but don't include necessary labels for opacity predictions, which is a real-world problem.
- Data visualization is key for our project, as smoke is an incredibly difficult problem Currently humans are in the real world, manually scoring opacities on cite, a to train a model, we need to understand what the model can see in the image. To address this, we have created gifs of the data, that show how a Machine Learning model can learn to focus on only the smoke in the videos.

Above is an example of true data (left), on a cloudy day, versus the extracted features of smoke (right). This is an example of how a computer can visualize the patterns of complex phenomena such as smoke.

During this semester, it has been found that smoke is inherently a very difficult problem for computers to solve. As smoke is unique to its environment, i.e., how it was emitted, backgrounds, or combustion type, even similar opacities may appear to look different. To counteract this, we have proposed and studied:

- More complex models than a convolutional neural network is needed, as the smoke itself can be lost as a feature. We have done comprehensive literature reviews to identify key architectures and components that may pick out the smoke and identify it correctly, even in unclear conditions.
- Cropping data to exclude unneeded features such as clouds or vehicles, in essence creating the dataset to exclude any feature that isn't smoke. While this works in the short term, a more robust model would learn to exclude these on its own.
- Expert results have been gathered and analyzed, to identify how humans predict a smoke opacity, and find areas of weakness, where humans tend to predict incorrectly. These cases may help us train the model to focus more heavily on certain areas, solving the hardest parts of the problems.

Research Plans

1. Finish creating a custom model, that obtains greater results than the baselines. This is the main step to overcome, with most of the building blocks in place.
2. Update figures and tables in the paper, to reflect changes in the custom architecture. Many of the current figures look outdated and need to be regenerated.
3. Publish a comprehensive Computer Vision paper at ECCV in February 2024. This will be the culmination of this phase of the project.

Publications

Currently in works.

Literature Cited

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