FireFly: A Synthetic Dataset for Ember Detection in Wildfire

USC Viterbi School of Engineering
Ming Hsieh Department of Electrical and Computer Engineering

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ESC Energy-Efficient, Secure, and Sustainable Computing

Introduction

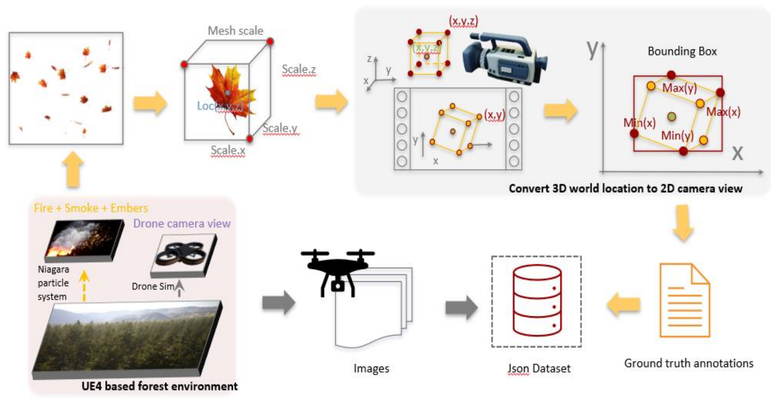
- During wildfires, embers can travel miles in wind and cause up to 90% of home ignition and damage
- Our ultimate goal is to detect and extinguish them before they approach the home ignition zone
- Many datasets for fire and smoke detection, but **0** public dataset for ember detection/tracking
- We present a **new synthetic dataset** for advancing drones to detect and later track embers.
- We have developed custom tools to automatically generate synthetic labeled dataset with dense small objects and make the parameters controlling the diversity of the data adjustable.
- We provided baseline performance **analysis for bounding box detection** results using state-of-the-art object detection models, We observed significant improvements in the mean Average Precision (mAP) detection metrics, with an increase of up to 8.57% compared to models that were trained solely on a smaller real dataset.

Solution

- **We use Unreal Engine 4 (a 3D computer graphics game engine) to generate all data, which has**
  - **Realistic rendering capacity**
    - **Makes domain transfer (simulation to real) for trained ML models potentially easier**
  - **Great flexibility for customizing the scenes**
    - **Allows us to vary a lot of aspects including the types of forest, the types of embers (burning leaves, sparks, etc.), day or night, seasons, weather**
  - **Ability to output detailed information about the embers**
    - **Allows us to provide exact ground-truth location of each individual embers in every image.**

Working space in UE4 - Coniferous forest sparks scenes

Workflow



- Encapsulating world: 3D forests background from UE4. Realistic rendering and physics engine restore wildfire scenes in forests under different atmospheric environments and visibility conditions
- Niagara particle system: Ember emitter; Parameters of embers controlled in blueprint script
- Camera: viewpoint simulating first-person view of unmanned aerial vehicle cameras
- Processing: 3d to 2d bounding box location for each ember in each frame. Annotations converted into COCO Json or YOLO dataset formats

Firefly Dataset

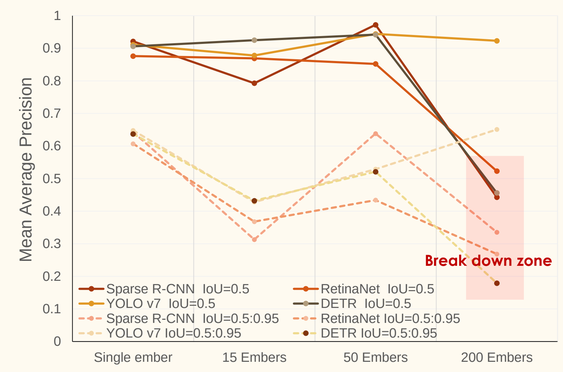
Ember Type	Scene	# Average Objects Per Frame	Ember Size	#frames
Burning Leaves	River/Dead Tree Forest[1]	1	Large	0.9k
	Pond/Dead Tree Forest	1	Small/Medium	0.7k
	Fog/Dry Wood/Dead Tree Forest	1	Large	0.7k
	Fog/Dry Wood/Dead Tree Forest	2	Medium	0.7k
	Fog/Dry Wood/Dead Tree Forest[2]	15	Small	1.2k
	Sunny[3]	50	Medium/Large	1.8k
Sparks	Cloudy Daytime/Tree Top	200	Medium	1.3k
	Evening Sunset/Heavy Smoke	200	Medium	1.7k
	Mist/Low Visibility	200	Medium	1.5k
	Night/Warm Temperature	200	Small	0.8k
	Daytime	200	Small	0.8k
	Night/Cold Temperature	200	Small/Medium	2.4k
	Mix Skylight/Temperature[4]	200	Small	2.4k
Empty	Evening Sunset Time/Sunny	0	NA	2.3k

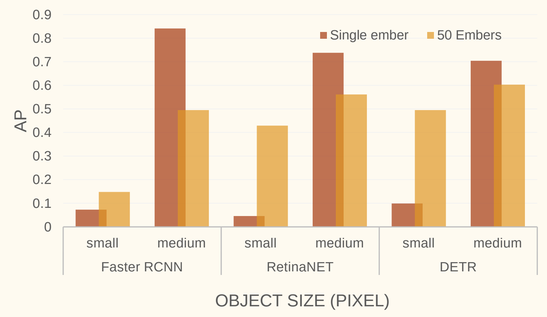
- The FireFly dataset comprises 20k frames: 17k positive with embers and 2.3k negative without. It's bifurcated into burning leaves and sparks, two prevalent forest fire ignition sources.
- Burning leaves has 6k frames, capturing autumnal scenes with varying ember sizes amidst environments like rivers, ponds, and hazy atmospheres. They're captured distant from fire fronts, with 1-50 targets per frame.
- Sparks, with 10.8k frames, captures various times of day and proximities to fire, with an average of 200 small, swift-moving targets per frame, categorized by size. Despite the skew towards positive samples (16.7k) versus negative (2.3k), it's to enhance training and reduce false negatives.

Metric

- Sparse R-CNN & RetinaNet: Efficient detectors; AdamW; LR: 2.5e-5; Weight Decay: 1e-4; RetinaNet uses focal loss.
- DETR: Transformer architecture, bipartite matching; AdamW; LR: 1e-2; Decay: 0.1/100 epochs.
- YOLOv7: Latest YOLO; SGD; LR: 1e-2; Momentum: 0.937.
- Performance Evaluation: mAP metric assesses detection accuracy at IoU thresholds (0.5 and 0.5:0.95) on different datasets.

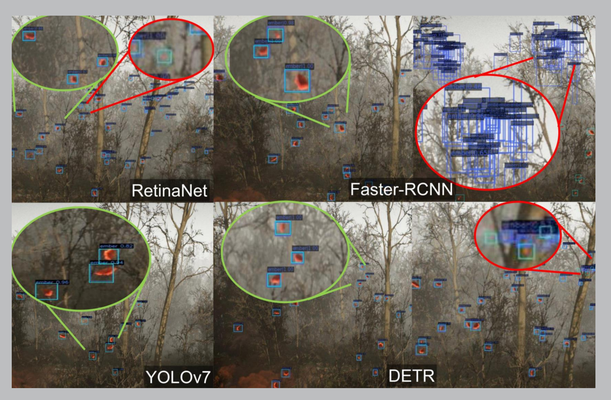
Comparative Analysis

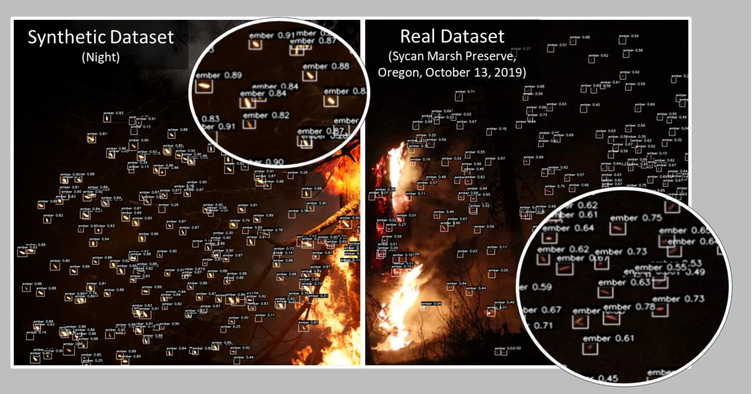




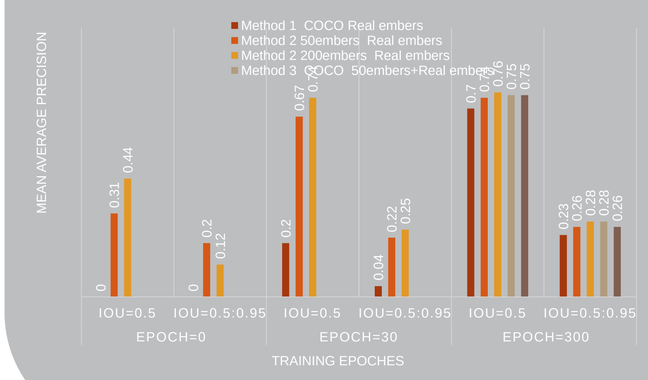
1. All four models exhibit commendable performance on synthetic subsets with 1, 15, and 50 embers per frame.
2. RetinaNet, Sparse R-CNN, and DETR face performance declines with increasing ember to 200 and decreasing size, due to limitations in small target feature learning and DETR's focus on global features. In contrast, YOLOv7, optimized for high-resolution input, demonstrates superior adaptability to such tasks.
3. Due to the attention mechanism in DETR, its receptive field is the whole image, and it is difficult to learn the features of the local area where the small target is located, which causes it to collapse the most among all models.

Evaluations in Real Ember Applications





Leveraging frames from U.S. Department of Agriculture wildfire videos, we developed a semi-automatically labeled dataset of 240 images and tests showed our synthetic data-trained model outperformed the COCO dataset-trained counterpart on real data.



Our exploration compared three training methods:

1. **Full supervised learning with COCO dataset pretraining and real ember dataset fine-tuning.**
2. **Transfer learning, utilizing synthetic datasets for pretraining and real ember datasets for fine-tuning.**
3. **A hybrid approach, blending synthetic and real-world datasets for comprehensive supervised learning.**

While Method 1 reached a mAP of 0.70 at IoU = 0.5, Method 2 surpassed this after just 30 epochs, attaining a peak mAP of 0.76—an 8.57% improvement. Method 3 scored the highest at 0.28 mAP with an IoU range of 0.5 to 0.95.

Conclusion

The tool and FireFly dataset form an effective framework for ML-based real-life wildfire ember detection.

- Tool Design: Developed a tool for auto-generating synthetic labeled datasets with adjustable parameters, focusing on dense small targets.
- Dataset Release: Introduced FireFly, a large-scale dataset with 20k diverse images for ember detection.
- Real Ember Testing: Demonstrated YOLOv7's effectiveness using FireFly; optimal mAP of 0.76 at IoU = 0.5.
- Performance Improvement: Achieved 8.57% higher mAP compared to using only a semi-automatically labelled real dataset.
- Efficiency: Our strategy results in higher accuracy with fewer epochs.

AUTHOR

Yue Hu[1] Xinan Ye[1] Yifei Liu[2] Souvik Kundu[3] Gourav Datta[1] Srikar Mutnuri[1] Namo Asavisanu[1]
Nora Ayanian[4] Konstantinos Psouni[1] Peter Beerel[1]
[1]University of Southern California [2]University of California, Irvine [3]Intel Labs, San Diego, USA [4]Brown University

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