Computer Vision-Guided Reinforcement Learning Approach to Source Localization

Christopher C Davis

Junior, University of Michigan

Abhishek P Dahad, Kimberlee J Kearfott

University of Michigan

Introduction and Motivation

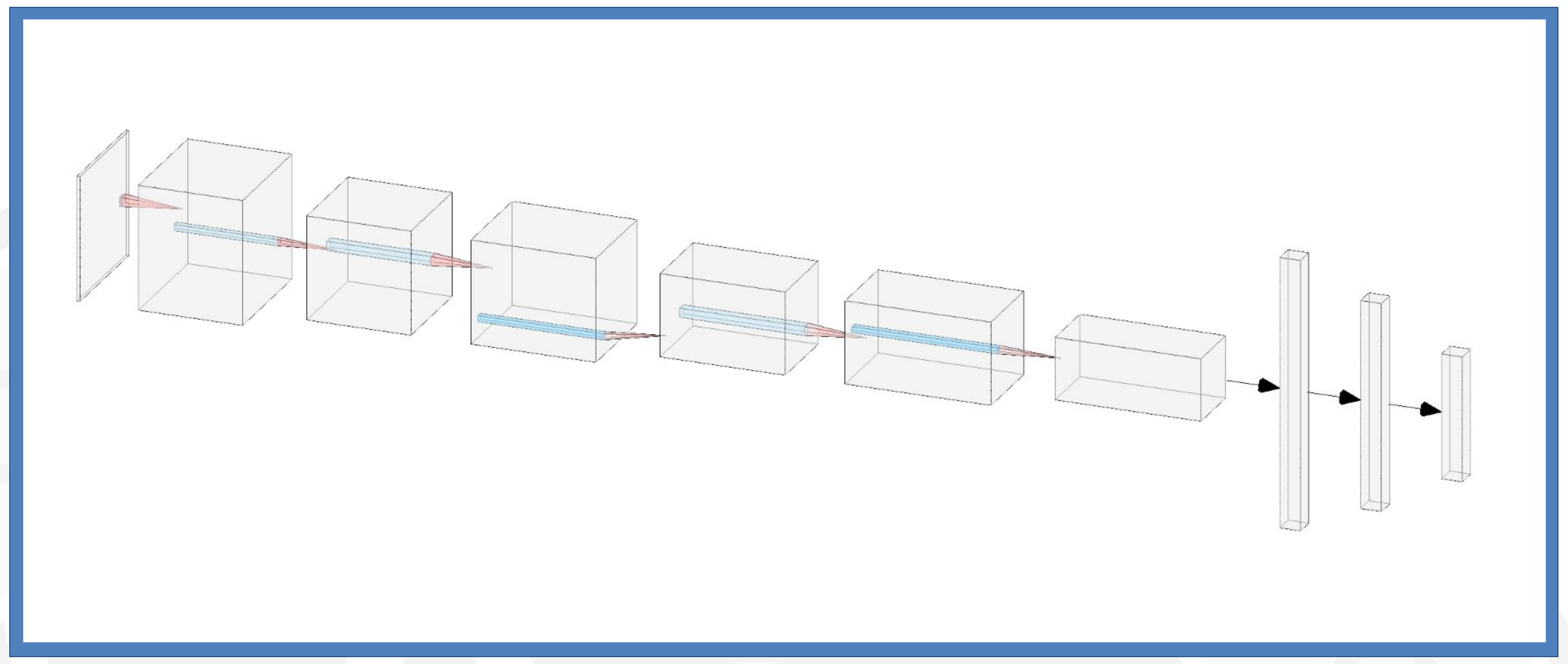
- ❑ Manual location of radiation sources is inefficient and potentially dangerous.
- ❑ Unmanned aerial vehicles (UAVs) eliminate dose, but uninformed navigation may be slow.
- ❑ Reinforcement Learning (RL) can intelligently pathfind, but more analysis needed to explicitly localize sources
- ❑ RL UAV paths can be considered biased random walks
- ❑ Given path observations, humans can intuitively estimate source locations (e.g. from heatmap)—a model can, too
- ❑ Treat path data as heatmap image, use computer vision techniques to replicate human intuition

Mission Relevance

- ❑ Efficient means of accurately and quickly exploring environments to detect illicit or lost sources
- ❑ Verification and monitoring of known radiation sources critical for material security and non-proliferation
- ❑ Improved post-incident radiological response
- ❑ Increased understanding of radiation background

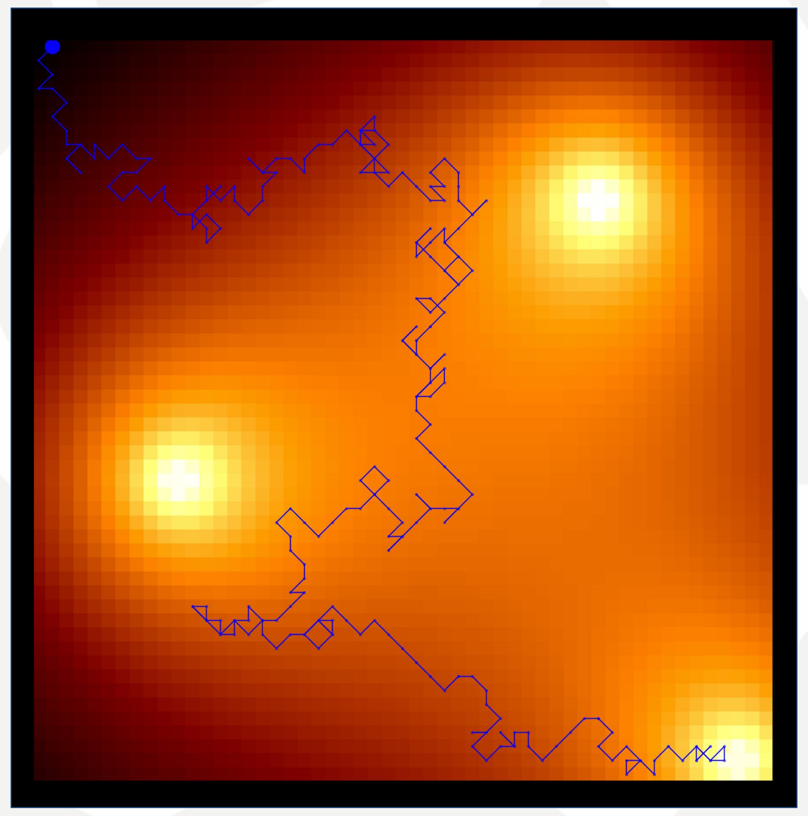
Technical Approach

- ❑ Most efficient localization paths are biased random walks
- ❑ Generate a count-rate heatmap from path samples
- ❑ Divide environment into arbitrary $n \times n$ cells
- ❑ Train a Convolutional Neural Network (CNN) to extract convolutional features in heatmap and "see" sources
- ❑ Feed features into CNN that classify each grid-cell with probability of having a source within it

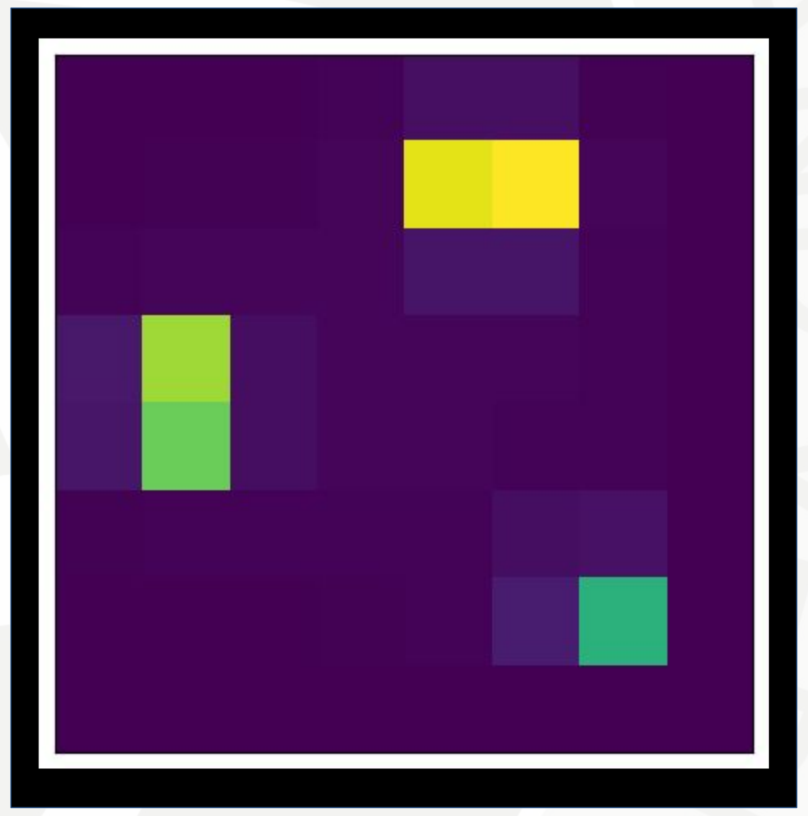


▲ CNN Model Architecture

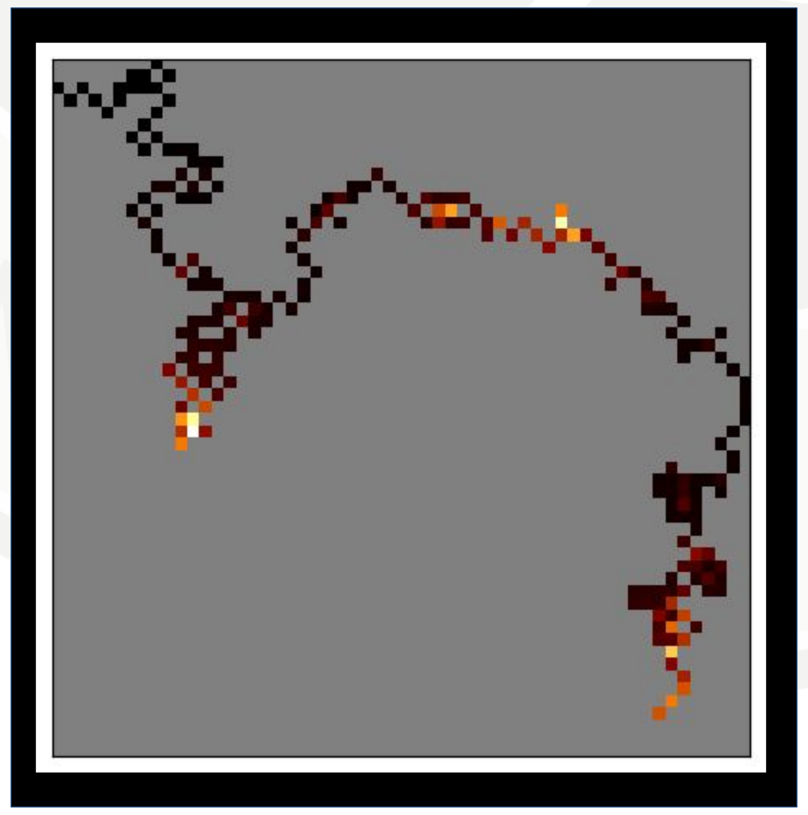
Results



▲ Sample RL Path (log scale)



▲ Classification (probability)



▲ Sample RL Path Data (log scale)

Sources	Path Length	Precision	Recall	F1
1	200	0.645	0.673	0.659
1	500	0.889	0.864	0.876
1	1500	0.956	0.955	0.955
2	200	0.712	0.714	0.713
2	500	0.893	0.89	0.891
2	1500	0.962	0.959	0.960
3	200	0.710	0.709	0.709
3	500	0.895	0.896	0.895
3	1500	0.981	0.942	0.961
4	200	0.777	0.768	0.772
4	500	0.901	0.901	0.901
4	1500	0.983	0.985	0.984

▲ Model Summary

Expected Impact

- ❑ More efficient approach than both traditional and algorithmic approaches
- ❑ Optimal analysis of mobile and sensor arrays
- ❑ Can be used to analyze any localization technique, including static sensor arrays
- ❑ Automates heatmap analysis

MTV Impact

Undergraduate students:

- ❑ Introduction to deep learning/computer vision
- ❑ Experience preparing and presenting work
- ❑ Possible journal article

Conclusion

- ❑ CNN model applies to any mobile platform, including manual searches
- ❑ Better with more data, applicable to static sensor arrays or drone swarms
- ❑ Easier to adapt to multiple sources than recursive, regression-based approaches
- ❑ CNN involves up-/downsampling, so must trade-off between input resolution (more samples), output resolution (more precision), and training time

Next Steps

- ❑ Utilize within pathing localization algorithms
- ❑ Introduce simple attenuating geometry
- ❑ Train adaptability on user-generated geometry

This work was funded in-part by the Consortium for Monitoring, Technology, and Verification under DOE-NNSA award number DE-NA0003920

National Nuclear Security Administration