Machine Learning for Object Detection and Classification for Multimodal Airborne Sensor Data

Chris Blackman, Supervised by Murat Uney (EEE), Yalin Zheng (Eye and Vision Sciences), David Greig (Leonardo UK Ltd.)
EPSRC Centre for Doctoral Training in Distributed Algorithms, University of Liverpool, Liverpool, UK

Background & Aims

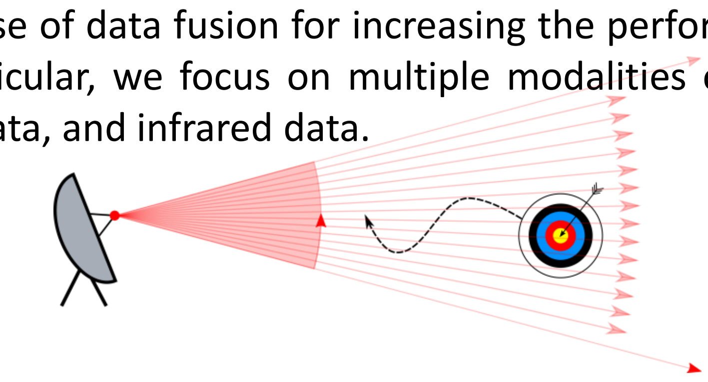
Machine learning (ML) for object detection and classification typically requires vast amounts of input data for training neural networks (NNs). Restricted contexts limit data availability and therefore application of ML. Leonardo UK is a defence and security company seeking to enhance their product capabilities by exploring the rapidly expanding solution space of ML. The focus of this work is to assess the viability of transferring learning between multiple data modalities, for example between radar and infrared sensor data, or multiple imaging resolutions from the same sensor.

Real-world surveillance presents unique conditions for data acquisition compared to lab testing. In general, classification performance improves with increased input quality [1]. Data fusion may allow improved classification [2] as multiple features can be learned.

DL techniques show promise for object classification in radar data [3]. Data fusion and object detection / classification for ocean surveillance using visible and infrared [2], SAR [4], satellite and remote sensing [4] improves classification. ML and DL for data fusion can improve classification [2] however data co-registration remains an issue [5].

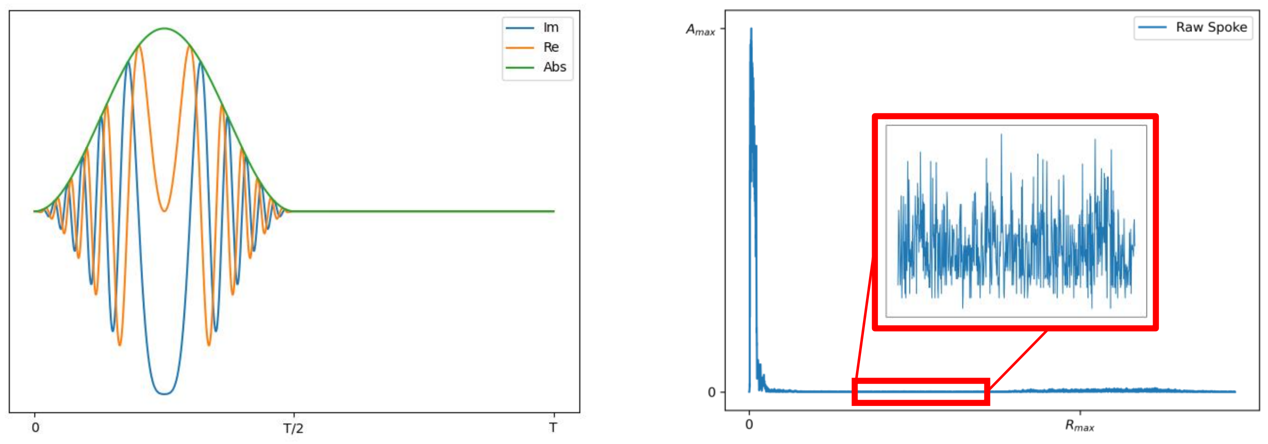
This topic is exciting as there are limited studies reported in the literature on pulse-Doppler (PD) radar data for ocean surface surveillance, and its fusion with either other modalities of the same radar, or that of other sensors.

Firstly, this work seeks to establish the viability of a classifier for multiple data modalities, but only trained on a subset of modalities. Secondly, we investigate the use of data fusion for increasing the performance of such a classifier. In particular, we focus on multiple modalities of pulse-Doppler radar data, AIS data, and infrared data.

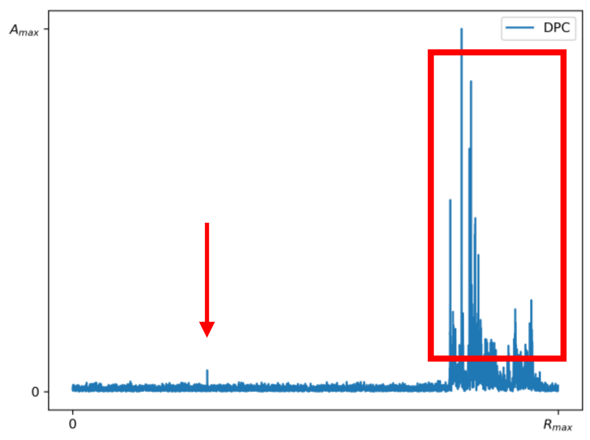


Methods & Preliminary Results

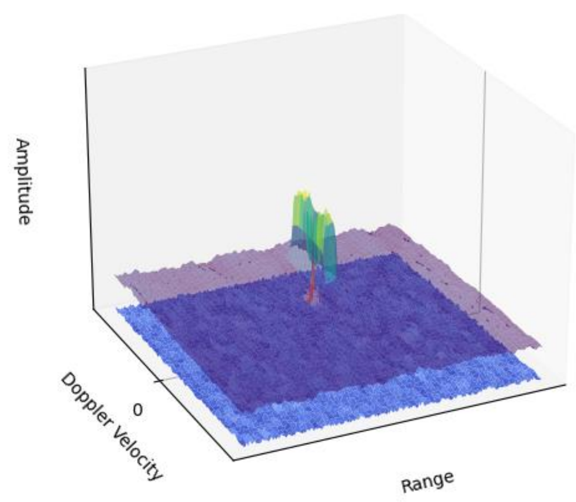
- Raw data unsuitable for detection. Transmitted pulse (left) and a single received signal (right). Many pulses in one direction (burst). Target peak not visible.



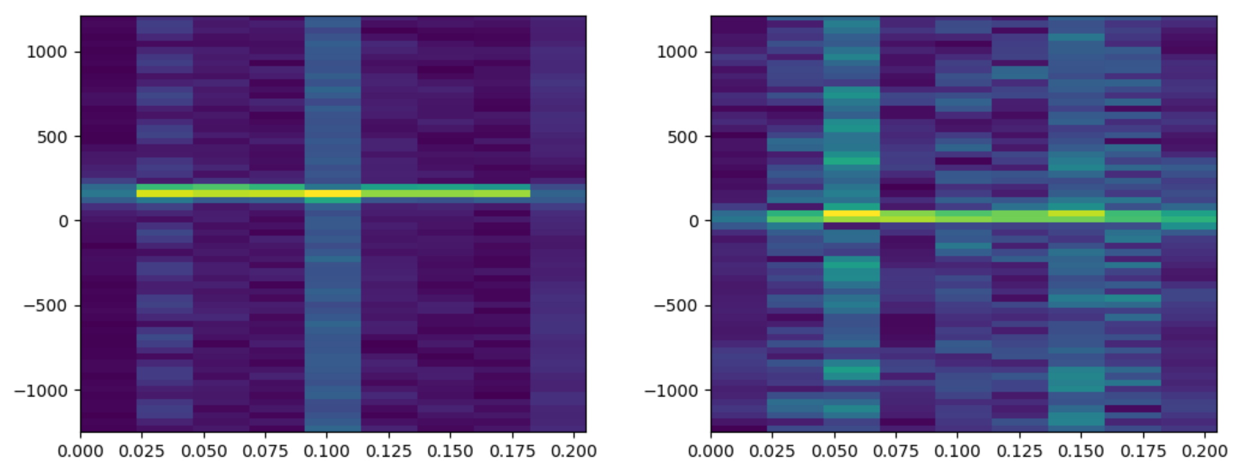
- Pulse compression, convolving transmitted and received signals, as a matched filter. Target peak visible (arrow), although dwarfed by clutter (boxed).



- FFT along range bins within burst (slow-time) to produce range-Doppler maps using phase data to detect moving targets in a ocean surface surveillance scene.
- Associated AIS and GPS data used to isolate some clutter.
- FFT-based CA CFAR algorithm implemented to adaptively filter noise from the scene, isolating target. This is computationally expensive.



- Downsampling range-Doppler map gives performance increase for CFAR but reduces data resolution.
- Unique micro-Doppler signatures visible after algorithmic processing.
- Ready for ML detection.



Future Work

We aim to use ML to identify unimodal features in the micro-Doppler signatures of objects in the surveillance area, classifying targets and clutter [3, 5, 6]. By combining this with features extracted from other data from a different modality, we will assess the relative performance of unimodal and multimodal classifiers developed using pulse-Doppler radar data.

Alternative methods of data fusion exist [2, 4], which may offer improved performance in either runtime or prediction accuracy. A key aim of the future work is to establish whether transferred learning can improve radar data object classification on different data modalities, including data from other sensors.

Conclusion

This project will explore the use of ML to improve object detection and classification for multiple modalities of ocean surveillance data, and the scope for performance improvement through data fusion.

References

[1] S. Dodge and L. Karam, Understanding How Image Quality Affects Deep Neural Networks. arXiv, 2016. [2] F. Farahnakian and J. Heikkonen, "Deep Learning Based Multi-Modal Fusion Architectures for Maritime Vessel Detection," Remote Sensing, 2020 [3] C. Wang, et al., "Deep Learning-Based UAV Detection in Pulse-Doppler Radar," IEEE Transactions on Geoscience and Remote Sensing, 2022 [4] S. Salcedo-Sanz et al., "Machine learning information fusion in Earth observation: A comprehensive review of methods, applications and data sources," Information Fusion, 2020 [5] Diamantidou, "Multimodal Deep Learning Framework for Enhanced Accuracy of UAV Detection," in Computer Vision Systems, 2019 [6] V. C. Chen, et al., "Micro-Doppler effect in radar: phenomenon, model, and simulation study," IEEE Transactions on Aerospace and electronic systems, 2006.

Engineering and Physical Sciences Research Council
UNIVERSITY OF LIVERPOOL
LEONARDO