Synthetic Aperture Radar Automatic Target Classification Processing Concept

M. Woollard, A. Bannon, M.Ritchie and H. Griffiths

This paper presents a new simulation and processing methodology based on open source tools to produce high fidelity Synthetic Aperture Radar (SAR) simulations of ground vehicles of varying types, as well as analysis of an applied Automatic Target Recognition (ATR) technique. This work is based around the RaySAR open source model and the outputs have been configured for both monostatic and bistatic geometries. Input CAD models of various military and civilian vehicles are used to produce the SAR imagery. This output imagery was then used to train a Tiny You Only Look Once (YOLO) Convolutional Neural Net (CNN) classifier. The classification success of the CNN applied was showed to produce significantly accurate results and the whole pipeline of processing enabled rapid evaluation of potential ATR methods against targets of choice.

Introduction: Synthetic Aperture Radar (SAR) is a cornerstone of modern Intelligence, Surveillance, Target Acquisition, and Reconnaissance (ISTAR) capabilities, proving a day-night long range remote sensing method with reduced weather sensitivity. SAR uses physical translation of a platform's antenna to increase the effective size of the antenna array by synthesising a much larger virtual aperture along the track of motion. This allows for high-resolution imagery to be produced without the use of impractically large physical antennas. Various reconstruction methods are available to recover the desired image, including for complex scenarios involving spatially diverse transceivers flying arbitrary tracks [1].

With the introduction of many diverse airborne and spaceborne SAR platforms, the focus of advances in SAR is usually in the signal processing domain. Vast quantities of raw data are produced during a single imaging pass, leading to a reliance on Automatic Target Recognition (ATR) to extract only the desired information with a high degree of accuracy and interpret complex scenes with autonomy.

In 1995, the Airforce Research Laboratories (AFRL) produced the moving and stationary target acquisition and recognition (MSTAR) data set [2]. This dataset has been incredibly useful for the research community to baseline new ATR methods and share the results for the common goal of moving the research field forwards. Often, new processing and classification concepts are developed, but due to lack of data they can not be validated. This letter aims to describe a method for rapidly producing high fidelity simulated SAR data that can then be used to accelerate the development of new ATR methods. The presented data was simulated to support the development of an ATR solution for an X-band linear FMCW radar on a Commercial Off-The-Shelf (COTS) UAV platform operating as a low cost ISTAR system.

The importance of high-quality SAR simulation data is clear when evaluating the costs associated with gathering real SAR images for specialist targets such as military vehicles, which are often prohibitive; it could also be hard to maintain a current up-to-date database. There are also significant obstacles to obtaining signatures for currently operational vehicles due to the obvious security concerns. Whilst simulated data for some civilian targets is available through the Civilian Vehicle Data Domes dataset [3], using this as part of the training set would introduce a bias between simulated military and civilian targets; this in turn would bias the model towards civilian/military target separation, yielding unrepresentative performance figures. As such, it was decided that a custom dataset would have to be generated in order to provide sufficient quantities of data for reliable classifier training.

SAR Imagery: The simulation presented here applies the recently released RaySAR [4] model that was developed by Stefan Auer, and subsequently released to the wider research community in Jan 2016 [5]. The simulator ingests CAD models for the desired ground targets to produce high fidelity simulated SAR imagery. The model is based on a ray-tracing methodology presented in [4] and is implemented in MATLAB; the ray-tracing backend used is a modified version of the PoVRay engine. The simulations take in a scene, which is composed of a CAD model representing targets, and various configuration factors for geometry and radar parameters.

A number of modifications were made to the base RaySAR release to facilitate runs on the Myriad high performance compute (HPC) environment at UCL. These include conversion to a pure command line interface, submission scripts to interact with the Grid Engine scheduler and job scripts to fully automate the process of generating imagery from a CAD model of a target. Given a set of flight paths and transmitter/receiver orientations, time series data can also be generated by the modified post-processing code for a wide range of use case scenarios.

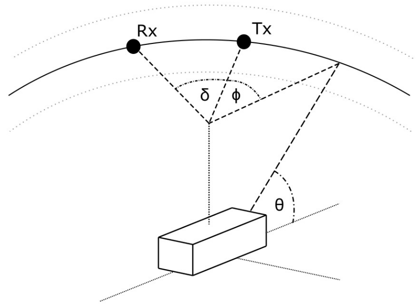

Fig. 1. Capture geometry illustration

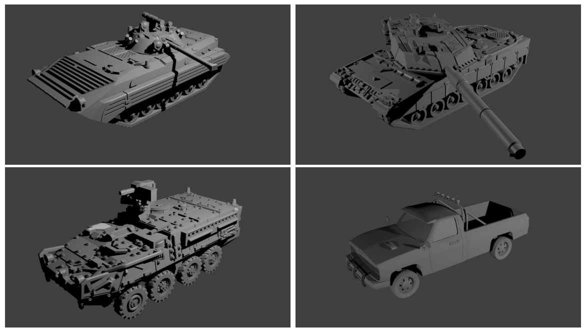

Fig. 2 *Examples of the 3D CAD models used as targets for training data generation (rendered in Blender)*

Figure 1 illustrates the structure of the data dome used to simulate imagery for each target. The 3D CAD model of each target was placed on a ground plane at the origin. The transmitter and receiver nodes were placed such that they were located on the surface of a $500\,\mathrm{m}$ sphere centred on the origin and lay in the same horizontal plane. The elevation angle θ was varied in $5°$ increments from $30°$ to $60°$, and the azimuth angle ϕ of the transmitter node was varied in $1°$ increments from $0°$ to $359°$. For the monostatic case, the transmitter and receiver were co-located ; for the bistatic cases, the receiver was offset by an angle δ from the transmitter in azimuth.

A demonstration database was created using six targets, including tanks (Leopard 2A6 and T72 B), armoured personnel carriers (BMP-2 and M1126 Stryker), an L33 self-propelled gun and a pick-up truck. For each of the six targets, a total of 35280 configurations were used (360 azimuth angles, 7 elevation angles, 14 bistatic angles). Where models could be posed, such as through the rotation of turrets or elevation of barrels, a number of poses were used. A selection of these models is presented in Figure 2. The SAR images were reconstructed from the raytracer output at a resolution of $0.15\,\mathrm{m}$ in both range and azimuth. All reconstructions were performed in slant range. Figure 3 shows examples of the simulated SAR images for a range of targets, with clear bistatic shadowing and multipath effects visible. This dataset was then divided to form segregated training and test sets; 30% of the images were selected at random to form the test set, and the remaining images constituted the training set.

ATR Results: A key goal of this analysis is to demonstrate how SAR imagery can be rapidly generated from complex CAD modules in a variety of geometries (including bistatic) and input to open source ATR methodologies to examine variations in predicted classification success across target types, radar parameters and geometries (including bistatic angle). To demonstrate this, a Convolutional Neural Network (CNN) classifier has been selected to discriminate the targets within the datasets. The selected CNN was the YOLO open source classifier network [6], which is normally applied to optical image object detection. The Tiny YOLO variant of the model was modified to use a single greyscale

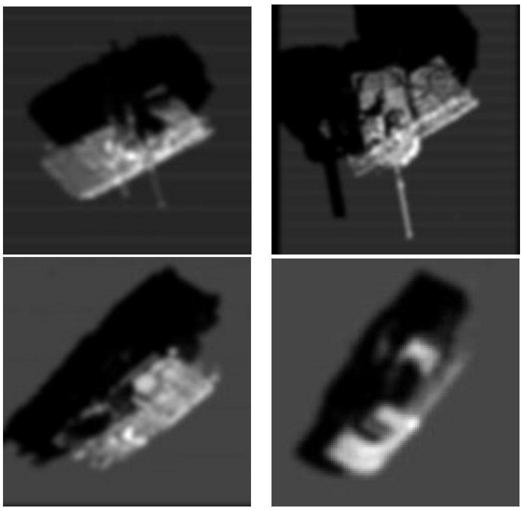

Fig. 3 *Examples of the target images generated with RaySAR at a resolution of 15 cm and a pixel spacing of 5 cm*

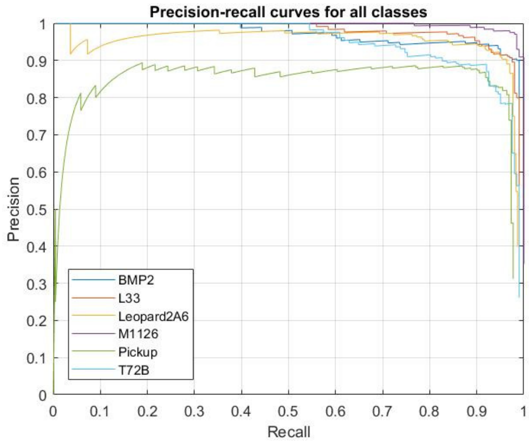

Fig. 4 *Precision-recall graph for the initial Tiny-YOLO model trained on 5000 labelled images with bounding boxes*

input channel instead of the stock RGB format. Changes were made to the non-maximal suppression process to improve suppression of multiple detections arising from single objects; this is possible because the vehicular targets considered are unlikely to overlap. This is in contrast to the original optical datasets used for the development of the YOLO architecture, where the bounding boxes associated with many smaller object categories may overlap with detections for larger objects (e.g. a pedestrian standing in front of a bus). The Tiny YOLO model was trained using 5000 images from the training set which were manually labelled with bounding boxes for the targets. The images were drawn randomly from all simulated geometries, and each class was equally represented within the set. 20% of these images were used as a validation set during training. A further 5000 images were drawn at random from the test dataset to evaluate the performance of the trained network. Figures 4 and 5 illustrate the precision-recall and receiver operating characteristic (ROC) curves associated with each class. It is evident that spurious detections are avoided even at high recall scores. Averaged F_1 and G scores of 0.9201 and 0.9210 respectively are achieved across the 6 classes when the confidence threshold was set to 0.3; an intersection-over-union threshold of 0.1 was set for successful detection. Performance is worst for the pickup target. It is theorised that this is due to three primary factors; the target is physically smaller than the armoured vehicles used, there are fewer obvious features which can be exploited by the classifier, and the open bed of the pickup gives rise to severe multipath artefacts that vary significantly depending on the observation geometry.

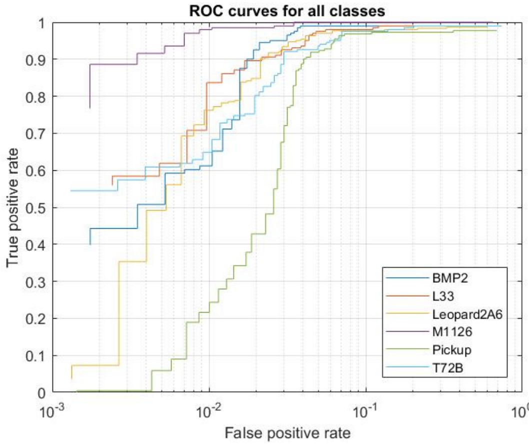

Fig. 5 *ROC curves for the initial Tiny-YOLO model trained on 5000 labelled images with bounding boxes*

Further work: As previously noted, there is considerable interest in the variations in ATR performance as the bistatic angle is changed. Some initial trials have shown promising results demonstrating different optimal angles for armoured and unarmoured vehicles. Analysis will also be performed on the relative classification success for the same target models in different poses. Tests using ground planes modelling realistic terrain via the diamond-square algorithm [7] have been successful, and may facilitate the simulation of large-scale scenes involving multiple targets.

Conclusions: The paper has presented a framework for simulating large volumes of high-fidelity SAR imagery containing vehicular targets. An example ATR approach has been demonstrated to provide promising results when trained using this imagery, which provides a basis for ongoing investigation into the effect of bistatic angle on classification success and its impact on mission planning for surveillance applications. The framework supports a number of active research routes related to ATR processing of SAR imagery, and will be actively maintained for the foreseeable future.

Acknowledgment: This work has been supported by The IET. The authors acknowledge the use of the UCL Myriad High Throughput Computing Facility (Myriad@UCL), and associated support services, in the completion of this work.

M. Woollard, A. Bannon, M. Ritchie and H. Griffiths (*EE Dept., UCL, London, UK*)

E-mail: michael.woollard.15@ucl.ac.uk

References

1 C. E. Yarman, B. Yazici, and M. Cheney, "Bistatic synthetic aperture radar imaging for arbitrary flight trajectories," *IEEE Transactions on Image Processing*, vol. 17, no. 1, pp. 84–93, 2008.
2 The air force moving and stationary target recognition database. [Online]. Available: https://www.sdms.afrl.af.mil/datasets/mstar/
3 K. E. Dungan, C. Austin, J. Nehrbass, and L. C. Potter, "Civilian vehicle radar data domes," in *Algorithms for synthetic aperture radar Imagery XVII*, vol. 7699. International Society for Optics and Photonics, 2010, p. 76990P.
4 S. Auer, S. Hinz, and R. Bamler, "Ray-tracing simulation techniques for understanding high-resolution sar images," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 3, pp. 1445–1456, 2010.
5 S. Auer, R. Bamler, and P. Reinartz, "Raysar-3d sar simulator: Now open source," in *Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International*. IEEE, 2016, pp. 6730–6733.
6 J. Redmon and A. Farhadi, "Yolo9000: better, faster, stronger," *arXiv preprint*, 2017.
7 G. S. Miller, "The definition and rendering of terrain maps," in *ACM SIGGRAPH Computer Graphics*, vol. 20, no. 4. ACM, 1986, pp. 39–48.