Automatic Target Detection and Recognition Using Synthetic Aperture Radar Imagery

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Importance of Image Exploitation

Defence forces rely upon a variety of sensor information to locate and track oppositional forces; the surveillance problem becomes particularly difficult over large land areas with sparse population centres and over the great expanse of the seas. The modern war-fighter is dependent upon several types of image data to aid in the surveillance task including optical data, infrared data, and radar data. The volume of image data would overwhelm the available image analysis capabilities unless the imagery is first pre-screened to detect and/or classify potentially significant military targets. The detection and/or classification problem increases in difficulty when the targets are small (eg, tanks, small watercraft, personnel carriers) and the surveillance area is large. Such an ATD/R system is not fully automated, rather is designed to cue the analyst where possible in order to reduce workload and fatigue, and possibly even reduce the number of analysts required to achieve mission objectives.

Radar imagery enjoys the advantage of independence from a passive illumination source, such as sunlight or starlight, thus offers imaging capability at night and through clouds. Modern day radar imaging systems are capable of comparatively high resolution by utilising synthetic aperture processing methods. The motivating requirement is to employ SAR imagery as an aid in finding comparatively small mobile or relocatable targets; the requirement is of course an all-weather one. The need is to detect targets, cue the analyst, classify/recognise targets, and identify targets if possible.

This presentation will address four areas: (i) Target Detection, (ii) Target Discrimination, (iii) Target Classification/Recognition, and (iv) Performance prediction against real world impairments. It has been found through experience that the computational burden can be significantly reduced with the Detection/Discrimination approach prior to Classification/Recognition/Identification. Numerous technical disciplines support of these basic objectives, such as speckle filtering, super resolution, effects of image compression, coherent change detection, and terrain segmentation and classification.

Automatic Target Detection and Recognition Overview

A number of related disciplines (eg image enhancement, feature extraction, pattern classification) intersect in support of Automatic Target Detection and Recognition (ATD/R) research. These may be considered and addressed separately, however, when the goal is end-to-end system design for an operational system it is crucial they all be addressed together when predicting final performance metrics. A complete image exploitation system typically consists of five stages plus related enhancement algorithms. The five stages are: Detection, Discrimination, Classification, Recognition, and Identification, as shown in Figure 1. These stages may require a multi-level security approach to properly handle data sensitivities and access. Image enhancement, such as speckle reduction filtering, may or may not be required at various processing stages. Related processing functions may include such requirements as terrain segmentation and road detection in order to preselect optimal parameters for the classification algorithms. Image management issues, such as database management and compression algorithms, underpin any modern image exploitation system.

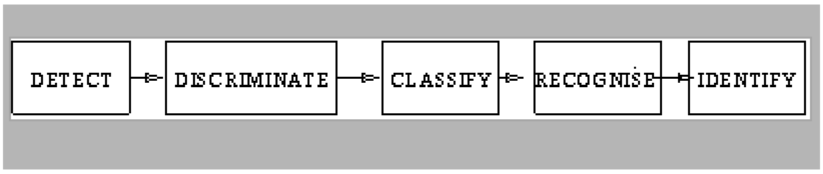

Figure 1. Automatic Target Detection/Recognition Processing Flow

The first step is the detection problem, which determines the presence of the target signatures in the sensor data (of SAR image in our case) and reliably differentiates targets from clutter. At this stage we are interested in determining and analysing features of target signatures, which are separable from background. Generally, if the background can be accurately modelled as a stationary random process, the detection problem is comparatively easy. The performance of detection decreases when targets are embedded in non-spatially homogeneous backgrounds or when the sensor data contains other man made objects. The Probability of Detection (PD) at this first stage must be as close to 100% as possible with the consequence that the Probability of False Alarm Rate is allowed to be comparatively high. This ensures that targets are not missed. As all image pixels are processed in the detection stage the detection algorithm must be computationally efficient. A typical target detection algorithm consists of a local threshold of pixel intensity, with the threshold set to maintain a specified Probability of Detection (eg PD = 90%) and an acceptable Probability of False Alarm or False Alarm Rate (eg 10 False Alarms/Sq Km). Unfortunately, increasing the Probability of Detection comes at the price of increased False Alarm Rate so the first stage detection statistics must be chosen with care.

After the detection stage the False Alarm Rate will be unacceptably high within any real world SAR imagery, thus it will be necessary to perform Target Discrimination in order to reduce the False Alarm Rate prior to Target Classification processing. Even in the most homogeneous terrain, such as grassland, some number of False Alarms will occur due to image noise and speckle. Speckle reduction filtering may or may not improve the situation as the filtering also affects the targets. SAR imaging systems vary significantly thus no blanket statements can generally be made concerning the need for speckle filtering. False Alarms also arise from manmade returns from windmills, agricultural fences, any metallic object such as a road sign, and commercial vehicular traffic. Ocean surveillance has its own set of phenomena related to the presence of small fishing boats, other unidentified shipping traffic, and sea state effects on the SAR image.

Since Target Discrimination is applied only to Regions of Interest (ROI) that passed through the first Target Detection stage, we may apply more sophisticated processing algorithms. Target Discrimination may be considered binary pattern classification, i.e. Target Present Vs Target Not Present. Such a viewpoint allows one to utilise the field of pattern recognition results to good effect in reducing False Alarm Rate. Target Discrimination is a key component of ant ATD/R system [4,7,8,9,10,11].

The third step is the classification problem. That is, can a target signature be reliably distinguished from signatures of other targets? This problem also includes distinguishing target signatures from those resulting from the clutter (buildings, trees, etc) and non-target objects (confuser vehicles, etc). In the Target Classification stage we desire to classify a target as belonging to a general class such as Tank or Armoured Personnel Carrier, as opposed to some non-militarily significant target. The Target Classification stage uses many of the same techniques of the Target Discrimination stage with the difference that in general it is no longer a binary classification problem and that the features used will likely be different. Although Target Classification is well understood in general and not too difficult for clean imagery, the problem becomes difficult when the targets are camouflaged, located under foliage, revetted, and/or mixed with urban clutter.

After Target Classification, one also desires to be able to recognise targets by type within a class. Target recognition is defined as automatically recognising a T-72 tank for example from the class of targets determined to be military tanks. The ability to do so depends on knowing the various target signatures, there being reasonable differences among those signatures, and having a sensor to be able to sense those differences. The variability of target signatures results from a number of factors. Since target location and orientation are not generally known in advance we must be prepared to detect and recognise targets at all positions and orientations (pose). Alternatively, pose invariant features of target signatures must be developed. Also, targets have parts that can articulate. Large metal pieces can significantly alter targets shapes and signatures. Smaller parts (such as hatches, guns, toolboxes, etc) also result in variations in target signatures. Determining, measuring and storing all the variations in target signatures is an ongoing task in ATR research and development efforts. Copious literature exists on ATR [1,2,3,5,6].

The basic ATR target detection, classification, and recognition stages can be subsequently be followed up by a Target Identification stage. Target Identification refers to the ability to precisely identify a target. For example, after determining that the target is a tank, the tank is a T-72, Target Identification would add that perhaps the T-72 is serial number 1357. It is generally the case that successful Target Identification requires all source data and data fusion techniques.

ATD/R Literature Review

This section highlights a few recent papers on the subject of ATD/R. No attempt is made at completeness, however, several of the listed references contain fairly extensive literature surveys.

Several approaches to ATR applied to SAR imagery are described in [19]. The performance achieved by each for a range of database complexities is studied and compared. These approaches are based on a likelihood test under a conditionally Gaussian model, log-magnitude least squared error, and quarter power least squared error. A framework is described for directly comparing these and related algorithms on an while minimising the impact of implementation details which could prejudice the results. This framework accounts for variation in image sizes, in angular resolution, and in the sizes of orientation windows used for training. All approaches are evaluated for wide range of parameterisations and the dependence on these parameters of both the resulting performance and the resulting database complexity is explored. Databases for all of the approaches are trained using identical sets of images and their performance is assessed under identical testing scenarios in terms of probability of correct classification, confusion matrices, and orientation estimation error. The results indicate that the conditionally Gaussian approach yields, on average better target orientation estimates than the other approaches at all database complexities. The approach yielding the best target recognition rate varies with the level of database complexity, with the conditionally Gaussian, normalised log-magnitude variants, and normalised quarter power approaches each yielding the best performance for some range.

A conditionally Rician model for the amplitudes of pixels in SAR images quantitatively that accounts for both specular and diffuse scatterers was considered in [18]. Conditionally Rician models generalise conditionally Gaussian models including means with uniformly distributed phases in the complex imagery. Using MSTAR data, the resulting performance for a number of four class ATR problems representing both standard and extended operating conditions is studied and compared the performance corresponding conditionally Gaussian models. Performance is measured quantitatively using the Hilbert-Schmidt squared error for orientation estimation and the probability of error for recognition. For the MSTAR dataset used, the results indicate that algorithms based on conditionally Rician and conditionally Gaussian yield similar results when a rich set of training data is available, but the performance under the Rician model suffers with smaller training sets. Due to the smaller number of distribution parameters, the conditionally Gaussian approach is able to yield better performance for any fixed complexity.

Automatic classification of targets in SAR imagery is performed in [17] using topographic features. Targets are segmented from wide area imagery using a constant false alarm rate detector. Individual target areas are classified using a Topographical Primal Sketch that assigns each pixel a label that is invariant under monotonic grey tone transformations. A local surface fit is used to estimate the underlying function at each target pixel. Pixels classified are based on the zero crossings of the first directional derivatives and the extrema of second directional derivatives. Multiple matching schemes are investigated including correlation and graph matching schemes that incorporate distance between features as well as similarity measures. Trade-offs between the different matching schemes is also addressed with respect to robustness and computational complexity.

A manual segmentation process using supervised quality control is introduced in [16]. Using 'goodness of fit' measures the quality of manual segmentation on SAR target chips is presented. Using the expected metrics associated with the manual segmentation process, the performance of automated segmentation techniques can be evaluated. The approach of using manual segmentation to evaluate the performance of automated segmentation techniques is presented demonstrating the results on simple automated segmentation technique that incorporates speckle removal and segmentation. ATR with high-resolution SAR imagery is considered in this paper. A prototype structural model-based system for SAR ATR is presented . The system achieved 98.9% of recognition rate. Target segmentation is based on image peaks and Delaunay triangulation. In the paper leading edges of a generic vehicle model for target azimuth estimation independent of target class are defined. Leading edges also form a target coordinate frame. Measurements with respect to this coordinate frame are quasi-invariant under rigid transformations. A two-step technique using hypothesis generation and iterative Newton-Raphson search is devised for efficient image alignment.

The authors in [22] describe a new architecture for SAR ATR based on the premise that the pose of the target is estimated within a high degree of precision. Three strategies of learning and representation to build the features are compared: support vector machine, quadratic mutual information cost function for neural networks, and a principal component analysis extended with multi-resolution. Experimental results using MSTAR dataset show better than template matching algorithm performance.

Finally, a number of approaches to the use of Support Vector Machines (SVMs) can be found in [24,25,26,27,28].

CSSIP Experience in ATD/R

CSSIP have extensive related experience in most aspects of Automatic Target Detection, Discrimination, and Classification/Recognition studies. We first will list the relevant technical areas for selected studies, followed by a brief illustration of the basic capabilities developed using MSTAR data. The WARS02 presentation will use results from these studies to illustrate a typical ATD/R system.

MSTAR Data-based Automatic Target Classification and Recognition Study

A two-year effort was directed at developing an initial capability within the field of Automatic Target recognition (ATR) from Synthetic Aperture Radar (SAR) MSTAR imagery. In addition to implementing benchmark algorithms from the open literature, we desired to identify areas of research that hold promise of improving ATR performance. The following tasks have been accomplished.

- Literature review completed to benchmark state-of-the-art ATR R&D.
- Template matching classification algorithm implemented.
- Two classifiers have been implemented: Linear Discriminant Analysis (LDA) and a Support Vector Machine (SVM).
- GUI demo software developed as a research tool for ATR and to highlight results conveniently for interested personnel.
- A Karhunen Loeve Transform (KLT) feature has been proposed.
- The position and orientation estimation algorithms have been developed (pose).
- The rigid transformation invariant (RTI) features based on Karhunen-Loeve Transform have been proposed, implemented and tested on MSTAR dataset with and without additive noise.
- The Mellin Transform (RTI) feature has been implemented and tested.
- The RTI features have been tested on reduced resolution SAR data, using embedded in Matlab image compression algorithms and the compression algorithm using wavelets.
- Other than KLT based MSE classifiers have been implemented and tested. These classifiers are Maximum Likelihood (ML) Classifier and Support Vector Machines (SVM) Classifier.
- An optimisation algorithm for multi-class SVM has been developed
- SVM Classification GUI has been written to accommodate for the SVM experiments.

JP129 Analyst Detection Support System Study

CSSIP successfully completed a two-year study program for Target Detection and Discrimination funded by the Australian Defence Force under program element JP129. The SAR data were collected in field trials using the indigenous Australian design and built INGARA radar system flying aboard a King Air twin-engine aircraft. Many of the results have been published in the open literature [4,7,8,9,10,11]. The Target Detection and Discrimination topics studied included the following areas.

- Literature review
- Speckle reduction algorithms
- Multi-scale autoregressive modelling techniques
- Singular value decomposition techniques
- Features from open literature papers
- Linear discriminant classifiers
- Support vector machine classification
- Hierarchies of classifiers
- Road detection algorithms
- Terrain segmentation algorithms

In most ATD/R studies the performance metric is typically Probability of Detection of correct Classification Vs. Probility of False Alarm. A confusion matrix is also utilised to show classification performance wherein the percentage of correct classifications are shown on the main diagonal and errors on the off diagonals. Figure 2. illustrates a typical result for classifying several MSTAR targets.

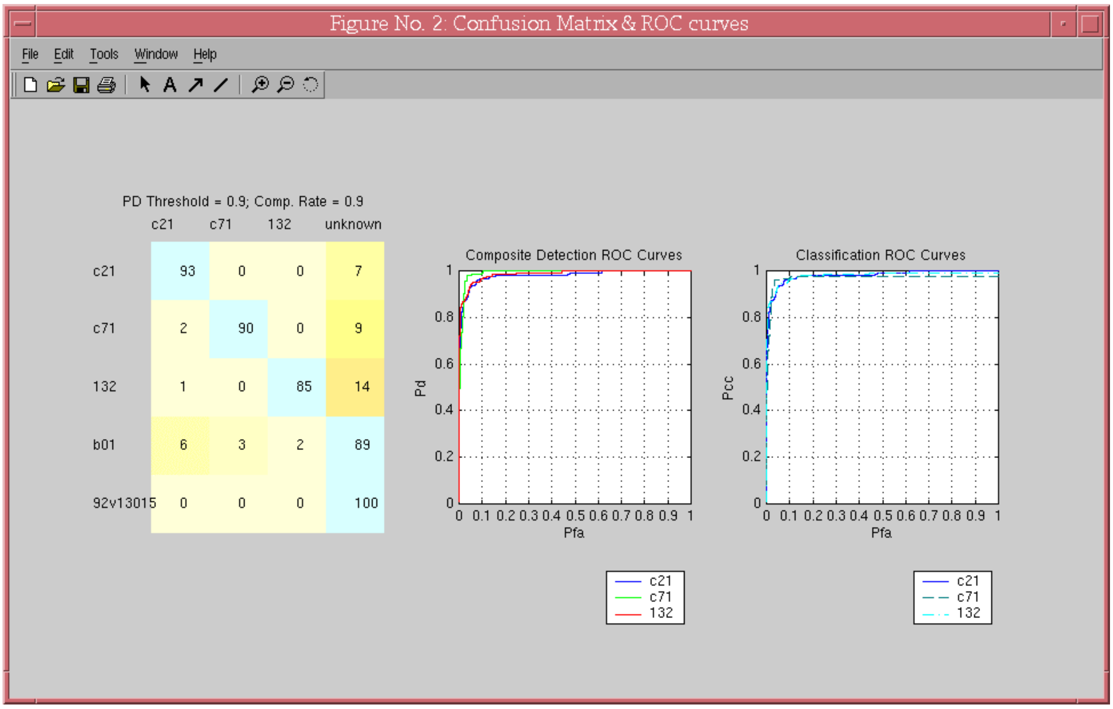

Figure 2. Classification Performance for Compression Rate 0.9

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