W-Band Maritime Target Classification using High Resolution Range Profiles

Tomasz Jasinski, Irina Antipov
Electronic Warfare and Radar Division (EWRD)
Defence Science and Technology Organisation (DSTO)
Edinburgh SA 5111, Australia

Sildomar T. Monteiro, Graham Brooker
Australian Centre for Field Robotics (ACFR)
School of Aerospace, Mechanical and Mechatronic Engineering
The University of Sydney
NSW 2006, Australia

***Abstract*—A W-band radar model was developed and tested using six point-scatterer maritime targets to assess the performance of four classifiers: traditional maximum correlation, naïve Bayes, polynomial kernel support vector machine (SVM) and radial basis function (RBF) SVM. W-band is characterized by scintillations caused by subtle aspect and range changes, making classification potentially problematic. High resolution range profiles (HRRPs) were used as the feature vectors with minimal pre-processing. Training and test datasets were generated by rotating the targets in the azimuth plane. A receiver operating characteristic (ROC) analysis was conducted, as well as precision, recall, and accuracy measures derived, and confusion matrices obtained for each classifier under a specific operating point. It was found that the traditional correlation approach performed best under the given circumstances, closely followed by the two SVM approaches and naïve Bayes. It was also found that different classifiers were better suited to classifying particular targets.**

Keywords—W-band; radar; classification; ATR; maritime

I. INTRODUCTION

A W-band arbitrary waveform, high resolution range profile (HRRP) radar model was developed in order to assess and further develop methods of classifying maritime targets. This task addresses two emerging trends in radar systems and automatic target recognition (ATR): the application of millimeter wave radar and the classification of targets using machine learning algorithms. In addition, this paper also explores some of the methods in assessing classifier performance.

The concept of using HRRPs for ATR is well established and has been thoroughly researched [1]-[5]. A particularly simple and elegant implementation is to use range profiles as feature vectors directly [3]. This approach is attractive in this application since it is applicable to any type of target, and can avoid complex, application-specific feature extraction methods which require significant "tuning" of parameters. So far, there has been limited application of these techniques to W-band radar, perhaps because of the assumption that classification performance would be unchanged. However, modern, high resolution, W-band radar systems have inherent characteristics that in some cases assist and in some cases hinder any attempt to apply machine learning. Scintillation effects caused by the interference of discrete scatterers are more prominent at higher frequencies, particularly when large targets are involved. In addition, the trend in modern radar systems to use finer resolutions implies more dimensions of data for machine learning algorithms, which are increasingly difficult to learn from due to the dreaded "curse of dimensionality".

There has been a steady increase in the adoption of modern machine learning algorithms by the ATR radar community. It is commonplace to see implementations of hidden Markov models [6], neural networks [7] and support vector machines [8] applied. Furthermore, hybrid implementations where ensembles of classifiers are used are also becoming common [7]. This increase in the complexity of classifiers will result in a corresponding increase in the complexity of assessment methods.

This paper presents some of the results obtained from the radar model in a maritime target classification application. Specifically, four common classifiers are compared: a classical correlation approach very common in the radar community; the naïve Bayes approach, a very common machine learning benchmark; as well as two, common non-linear support vector machine kernels: the polynomial kernel and the radial basis function (RBF) kernel. In each case, range profiles have been applied as feature vectors, with minimal pre-processing. It should be noted that optimum classifier performance is not the aim here, but rather to contrast four different classifiers in a given application. In the case of correlation, training is achieved by averaging range profiles within the training set. Training in the case of the naïve Bayes and SVM classifiers is achieved conventionally. Assessment of both classifiers is initially carried out using an accuracy versus signal-to-noise ratio (SNR) chart. Standard statistical metrics, such as a receiver operating characteristic (ROC) curve and confusion matrices, are then used to contrast the six targets and four classifiers. Classification is based on the highest score achieved by each target for each classifier.

II. RADAR MODELLING & SIMULATION

Maritime high resolution radar target recognition presents some unique problems for modern classifiers. Firstly, when dealing with fine range resolutions across large maritime

This work has been sponsored by the Defence Science and Technology Organisation (DSTO)

targets, there are many feature vectors to process. This is not only computationally intensive, but presents the classifier with an increasingly large feature space to deal with. Secondly, the small size of range bins means that small aspect variations result in scatterers crossing into different range bins. This disrupts the machine learning process, as key features can move between feature vectors. Finally, at W-band, scintillation effects from the Doppler contributions of multiple scatterers in any range bin can be ten times as large as the more conventional X-band radar for a given target rotation, since the frequency is ten times greater. This results in deep fading of the features, even for very small changes in aspect or range. This is particularly prominent for large targets where the scatterers are separated by a large cross range. For two scatterers separated in cross range by δr_c, rotating at an angular rate ω, at a carrier frequency f, the resulting Doppler modulation is [9]:

$$\delta f_D = \frac{2}{c}\omega \delta r_c f \tag{1}$$

Consequently, in order to accurately represent scintillation and individual scatterer Doppler components, a point-scatterer model was used to represent each of the six targets. Details of each target model are shown in Table I. It should be noted that only two pre-processing steps have been carried out: the normalization of data to the highest peak and the removal of invariant features, which are defined as range bins that don't ever contain more than 5% of peak power. For some targets, this represents a dramatic reduction of feature vectors.

The radar return or radar cross-section (RCS) from each scatterer in one simulation step is the sum of all scatterers (k) in that cell:

$$\sigma_{i,m} = \sum_{i=1}^{k} A_{i,m} e^{j2\pi f_m t + j\varphi_{i,m}} \tag{2}$$

where $A_{i,m}$ is the scatterer amplitude, f_m is the radar frequency at the m-th simulation step, and φ is the phase change due to position offset. The key radar model specifications are provided in Table II.

TABLE I. SIMULATED TARGET MODELS.

Target	***No. of Scatterers***	***Simulated Range Extent (m)***	***Range Bins***	***Feature Vectors***
Trawler	500	13.05	87	28
Oil Rig	500	91.05	607	17
Tanker	500	312	2080	19
Oiler	500	195	1300	240
Fishing Vessel 2	500	19.5	130	41
Fishing Vessel 1	500	32.55	217	131

TABLE II. RADAR MODEL SPECIFICATIONS.

Parameter	***Value***
Frequency	94GHz
Bandwidth	1000MHz
Waveform Type	Single Pulse
Target Range	1000m
Detector	Complex envelope
Polarization	N/A

Each target was tested at a fixed range to avoid any need for alignment. The resulting simulated range profiles for each target at zero aspect and one thousand meter range are shown in Fig 1. It should be noted that although alignment of profiles is a difficult task in practice, here it is simply assumed in order to avoid any effects resulting from misalignment. Typical fluctuations in range profiles for large rotations for a single target type are shown in Fig 2. Typical interference (scintillation) effects seen at W-band for very small aspect and range changes are shown in Fig 3.

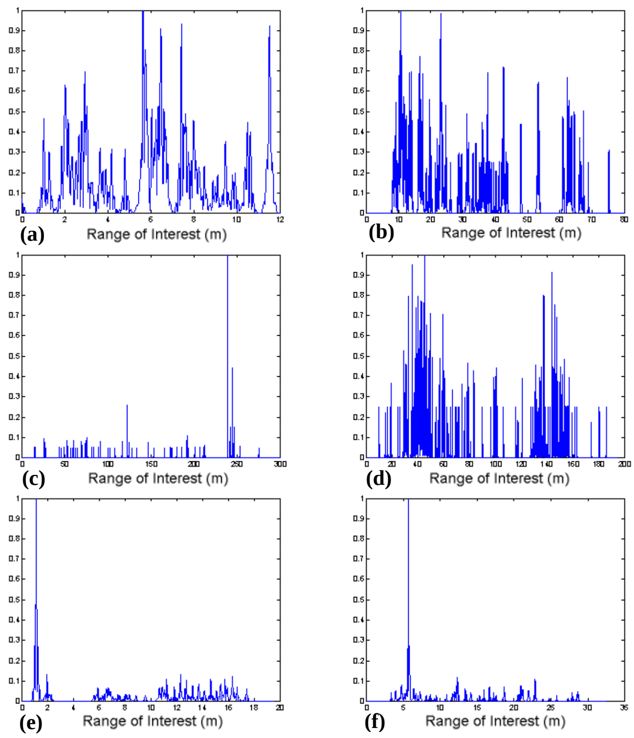

Figure 1. *Simulated HRRPs of the six target models, (a) trawler,(b) oil rig, (c) tanker, (d) oiler, (e) fishing vessel 2, (f) fishing vessel 1.*

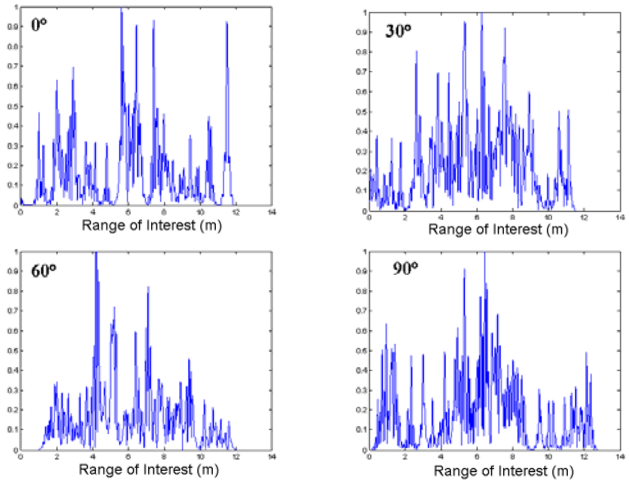

Figure 2. *HRRP resulting from rotating the Trawler target though various azimuth angles.*

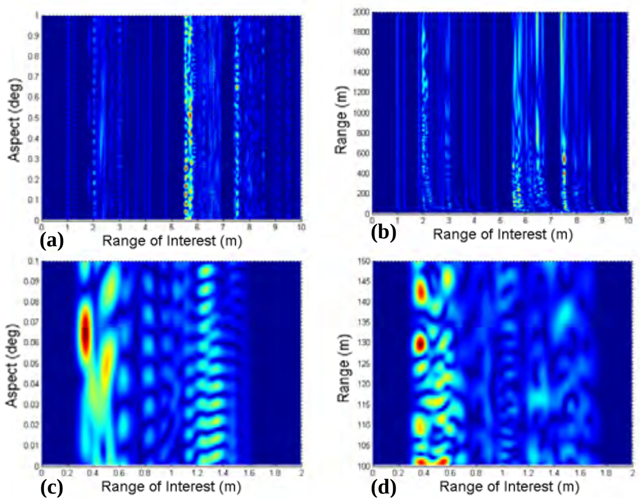

Figure 3. *(a) Modelled radar return for a rotating target, (b) modelled radar return as a function of range, (c) zoomed-in view of dominant target scatterer throughout target rotation, (d) zoomed-in view of dominant target scatterer as a function of range.*

III. METHODS FOR TARGET CLASSIFICATION

A. *Correlation*

Given two real valued waveforms, *f(n)* and *g(n)*, the normalized correlation coefficient is defined as [3]:

$$C(f,g)=\frac{\left|\frac{1}{n}\sum_{i=1}^{n} f(n)g(n)\right|}{\left|\frac{1}{n}\sum_{i=1}^{n}|f(n)|^2\frac{1}{n}\sum_{i=1}^{n}|g(n)|^2\right|^{\frac{1}{2}}} \tag{3}$$

B. *Naïve Bayes*

The posterior probability for the naïve Bayes classifier is defined as [10]:

$$P(C\,|\,F_1,\ldots.F_n)=\frac{1}{Z}\,p(C)\prod_{i=1}^{n}p(F_i\,|\,C) \tag{4}$$

Where C is the class and F_n are the features, and Z is the evidence used for normalizing the result [10]:

$$Z=\sum_{i=1}^{n}\left(p(C_i)\prod_{j=1}^{m}p(F_j\,|\,C_i)\right) \tag{5}$$

The class priors, *p(C)* are assumed to be equi-probable in this paper but have been left as variables in this section for completeness.

Since the features are continuous, the likelihood has been defined here according to a Gaussian distribution [10]:

$$P(F_i=v\,|\,C)=\frac{1}{\sqrt{2\pi\sigma_C^2}}e^{-\frac{(v-\mu_C)^2}{2\sigma_C^2}} \tag{6}$$

Where μ_c is the class mean, and σ_c is the class standard deviation.

C. *Polynomial Kernel SVM*

Equations for implementing the SVM have been left out since they are lengthy and easily obtained from most machine learning textbooks. The standard polynomial kernel function [11] utilized is provided below, where $\mathbf{x}_i$ and $\mathbf{x}_j$ are indexed data points and p is a constant (equal to 0.9 in this case):

$$K(\mathbf{x}_i,\mathbf{x}_j)=(\mathbf{x}_i\mathbf{x}_j+1)^p \tag{7}$$

D. *Radial Basis Function Kernel SVM*

As above, details of the SVM implementation have been left out due to their length. The radial basis function (RBF) kernel [11] that has been used is shown below, where $\mathbf{x}_i$ and $\mathbf{x}_j$ are indexed data points and σ is a constant (equal to 100 in this case):

$$K(\mathbf{x}_i,\mathbf{x}_j)=\exp\left(-\frac{1}{2\sigma^2}\left\|\mathbf{x}_i-\mathbf{x}_j\right\|^2\right) \tag{8}$$

IV. CLASSIFER PERFORMANCE MEASURES

Results from a classification task fall into 4 categories: true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). The following standard measures have been used to assess classification performance [12]. The TP rate (or recall) is defined as the ratio of correct positive classifications to all actual positive instances:

$$TP\ Rate/\mathrm{Re}call=\frac{TP}{TP+FN} \tag{9}$$

The FP rate is defined as the ratio of false positive classifications to all actual negative instances:

$$FP\ Rate=\frac{FP}{FP+TN} \tag{10}$$

Precision is defined as the ratio of correct positive classifications to all positive classifications made:

$$\Pr ecision = \frac{TP}{TP + FP} \tag{11}$$

F-measure (in this case F1) is also known as the harmonic mean of precision and recall:

$$F1 = \frac{2 \times \Pr ecision \times \mathrm{Re}call}{\Pr ecision + \mathrm{Re}call} \tag{12}$$

Accuracy is defined as the ratio of all correct classifications (positive and negative) for the entire test set:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{13}$$

This measure has also been used in this paper for multi-class assessment, where it is the total for all classes.

V. Simulation Results

A. *Generating Training and Test Data*

The training set was generated by drawing forty equally spaced samples from an aspect of zero to four degrees at a one-tenth of a degree separation. For each aspect, a simulation was conducted that resulted in a range profile. This was repeated for all six targets. All four classifiers were then trained on the resulting range profiles. The test set was made up of two-hundred and forty range profiles, each corresponding to a randomly selected test aspect, uniformly drawn from a zero to four degree range of a randomly selected target.

For the test set, all selected aspects were input into the simulation for all targets, resulting in two hundred and forty test profiles. All classifiers were trained and tested using the same data. Fig 4 shows the full training data for all classifiers for two arbitrary feature vectors. In this plane, some classes, such as the trawler and oiler appear easier to isolate even using a simple linear classifier than others, such as the oil rig and fishing vessel 2.

B. *Noise Performance*

Simulations were repeated for various levels of noise in the range profiles. Fig 5 shows the classifier performance (combined accuracy of all of the classes) as a function of signal-to-noise ratio (SNR). It should be noted that the accuracy of individual targets may be much lower or higher than the overall measure. It can be seen that the correlation method performs consistently most reliably. At a mid-range SNR of 12dB, in terms of combined accuracy the correlation classifier performs about 16% better than the RBF SVM, 30% better than the polynomial SVM, and 35% better than the naïve Bayes classifier.

a. *Receiver Operating Characteristic (ROC) Analysis*

A set of ROC curves were generated in order to assess individual target classification performance for multiple operating points. The discrimination threshold used to achieve these plots was the correlation coefficient for the correlation classifier; posterior probability for the naïve Bayes classifier; and distance from the separating hyperplane for the SVM classifiers. Fig 6 shows the ROC curves for all classifiers for a SNR of 12dB. It should be noted that the diagonal from bottom left to top right of each plot represents performance expected from random guessing. Any points above this diagonal represent performance that is better than random guessing, while curves below this line represent performance that is worse. It is interesting to note that different classifiers were more suited to classifying different targets. This was predicted following the results of Fig 4. The RBF SVM and naïve Bayes classifiers struggle with the trawler target, which poses little challenge to the correlation and polynomial SVM classifiers. The naïve Bayes classifier struggles with the tanker target, while for all other classifiers this was a relatively easy class.

b. *Confusion Matrices*

Table III, Table IV, Table V and Table VI show confusion matrices for both classifiers for a SNR of 12dB. As in the previous section, it is evident that certain classifiers are particularly effective or ineffective at dealing with particular targets. Most notable is the inability of any trawler or tanker classifications (whether true or false) to be made by either of the SVM classifiers. The naïve Bayes classifier, as is also evident in Fig 6, fails to classify the oiler target. It can also be seen that different classifiers tend to mistake various other classes for a particular favourite class. For example, the naïve Bayes classifier made seventy-three oil rig misclassifications. The RBK SVM also favored this class, while the polynomial SVM made one hundred and five oiler misclassifications.

C. *Two Class Comparison*

Fig 7 shows all performance measures for the entire operating range for the most successful classifier; correlation, and for the easiest and hardest targets to classify; the fishing vessel 2 and the oil rig respectively. The most notable difference is that for high thresholds in the correlation coefficient, the precision for the oil rig falls to zero, while reaching one for the fishing vessel 2. Similarly, recall remains at full scale for the oil rig target to almost a perfect correlation threshold. The F-measure consequently follows the same trend.

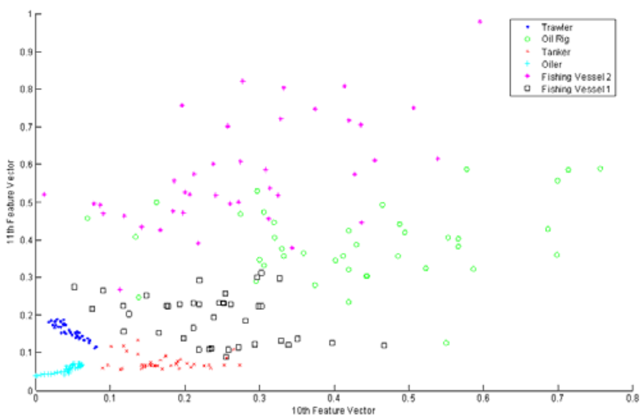

Figure 4. *The full training set shown in two-dimensional feature-space (the 10^{th} and 11^{th} features were selected arbitrarily).*

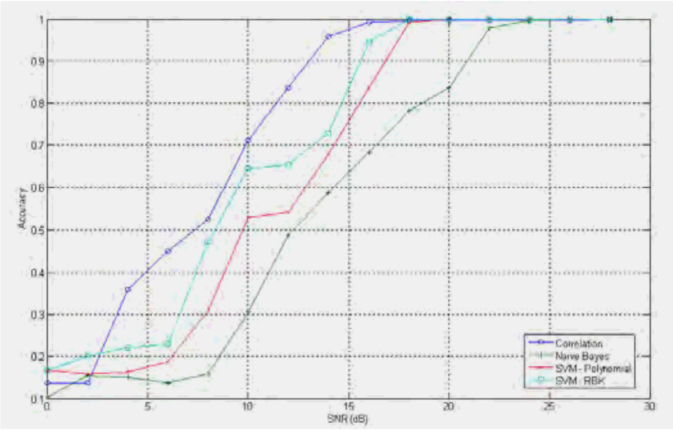

Figure 5. *Combined accuracy for all classes as a function of signal- to-noise ratio (SNR) for all four classifiers*

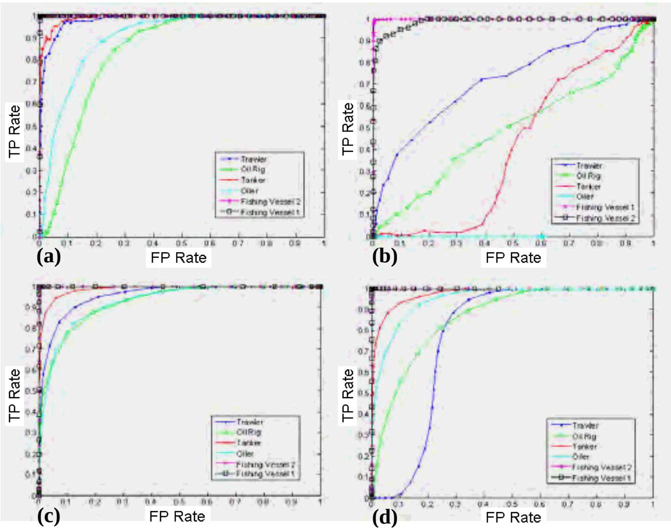

Figure 6. *ROC Analysis for all targets at an SNR of 12dB, (a) correlation, (b) naive Bayes, (c) polynomial SVM, (d) RBF SVM.*

TABLE III. CONFUSION MATRIX FOR THE CORRELATION CLASSIFIER AT A SNR OF 12DB.

Actual Class	***Classifier Result***					
	Tra wler	Oilrig	Tanker	Oiler	Fish2	Fish1
Trawler	29	4	0	0	0	0
Oil Rig	9	37	0	2	1	0
Tanker	1	3	26	0	0	0
Oiler	13	4	1	17	2	2
Fish2	0	0	0	0	44	0
Fish1	0	0	0	0	0	45

TABLE IV. CONFUSION MATRIX FOR THE NAÏVE BAYES CLASSIFIER AT A SNR OF 12DB.

Actual Class	***Classifier Result***					
	Tra wler	Oilrig	Tanker	Oiler	Fish2	Fish1
Trawler	2	31	0	0	0	0
Oil Rig	11	37	0	0	0	1
Tanker	2	24	4	0	0	0
Oiler	18	18	3	0	0	0
Fish2	0	0	7	0	37	0
Fish1	0	2	8	0	0	35

TABLE V. CONFUSION MATRIX FOR THE POLYNOMIAL SVM CLASSIFIER AT A SNR OF 12DB.

Actual Class	***Classifier Result***					
	Tra wler	Oilrig	Tanker	Oiler	Fish2	Fish1
Trawler	0	1	0	32	0	0
Oil Rig	0	6	0	43	0	0
Tanker	0	0	0	30	0	0
Oiler	0	0	0	39	0	0
Fish2	0	0	0	0	44	0
Fish1	0	0	0	0	0	45

TABLE VI. CONFUSION MATRIX FOR THE RADIAL BASIS FUNCTION SVM CLASSIFIER AT A SNR OF 12DB.

Actual Class	***Classifier Result***					
	Tra wler	Oilrig	Tanker	Oiler	Fish2	Fish1
Trawler	0	33	0	0	0	0
Oil Rig	0	49	0	0	0	0
Tanker	0	25	0	5	0	0
Oiler	0	15	0	24	0	0
Fish2	0	0	0	0	44	0
Fish1	0	0	0	0	0	45

VI. CONCLUSION AND FURTHER WORK

All four classifiers were contrasted using a developed W-band radar model. A combined-class accuracy measure revealed that the most effective approach was correlation, followed by RBF SVM, polynomial SVM and finally naïve Bayes. However, it should be highlighted that since machine learning approaches are known to be heavily dependent on the particular application as well as the pre-processing and feature extraction methods used, this result only applies to the particular configuration tested.

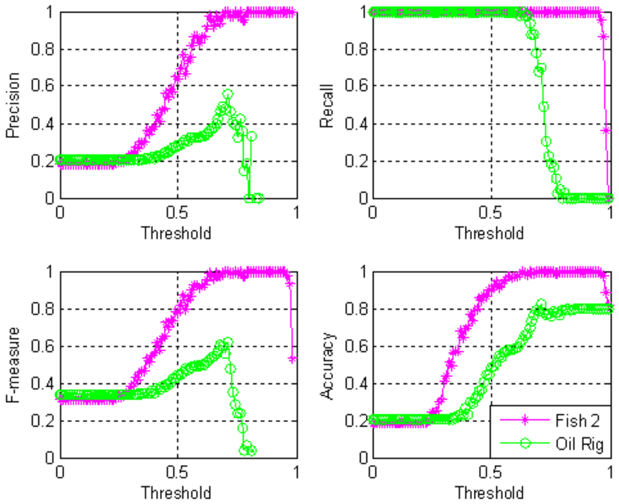

Figure 7. *Precision, recall, F-measure and accuracy for the oil rig and fishing vessel 2 using the correlation classifier.*

It was also found that the performance of each classifier was heavily target dependent. Not only was this reflected in correct classification rates, but also in the tendency of a target to be regularly mistaken for others. This finding suggests that an ensemble of classifiers may yield promising results for this application.

These simulations will be followed up with measurements of real maritime targets, and the assessment repeated. Another future work is to extend the simulations (and measurements) to collect range-Doppler profiles, resulting in two-dimensional profiles or Inverse Synthetic Aperture Radar (ISAR) images.

REFERENCES

[1] Tait, "Introduction to Radar Target Recognition", IEE Radar, Sonar, Navigation and Avionics Series 18, 2005.

[2] Currie, Brown, "Principles and Applications of Millimeter-Wave Radar", Artech House, 1987.

[3] Li, Yang, "Using Range Profiles as Feature Vectors to Identify Aerospace Objects", IEEE Transactions on Antennas and Propagation, Pages 261-268, Vol 41, No 3, 1993.

[4] Zyweck, Bogner, "Radar Target Classification of Commercial Aircraft", IEEE Transactions on Aerospace and Electronic Systems, Pages 598-606, Vol 32, No 2, 1996 .

[5] Williams, Westerkamp, Gross, Palomino, "Automatic Target Recognition of Time Critical Moving Targets using 1D HRR Radar", IEEE Aerospace and Electronic Systems (AES) Magazine, Pages 37-43, 2000.

[6] Nishimoto, Liao, Carin, "Target Identification from Multi-Aspect High Range Resolution Radar Signatures Using a Hidden Markov Model", The Institute of Electronics, Information and Communication Engineers (IEICE) Transactions, Pages 1706-1714, Vol E87, No 10, 2004.

[7] Robinson, Mahmood, Azimi-Sadjadi, Salazar, "Multi-aspect Target Discrimination using Hidden Markov Models and Neural Networks", IEEE Transactions on Neural Networks, Pages 447-459, 2005.

[8] Li, Weida, Licheng, "Radar Target Recognition based on Support Vector Machines", Proceedings of the International Conference on Signal Processing (ICSP), Pages 1453-1456, 2000.

[9] Wehner, "High Resolution Radar", Artech House, 1987

[10] Naïve Bayes Classifier, Wikipedia, http://en.wikipedia.org/wiki/Naive_bayes

[11] Veksler, "CS434a/541a: Pattern Recognition", Lecture 11, The University of Western Ontario.

[12] Cunningham, P, "ECML/PKDD 2009 Tutorial on Evaluation in Machine Learning", University College Dublin, European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases, 2009.