Target recognition for airborne bistatic radar using PCA

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Abstract

Target recognition is desirable feature of any defence radar system. With the present revival of interest in bistatic and multi-static radar systems, the future radar systems are predicted to invariably have bistatic abilities. The present project aims at looking into prospects and limitations of bistatic target recognition and to develop efficient algorithm for the same. The work in this paper reports the development of a database of bistatic target signatures, and the application of principal component analysis (PCA) based classifiers on the same. Results are compared with the more basic conditional Gaussian model based Bayesian classifier.

Keywords: Bistatic airborne radar, target recognition, PCA.

Introduction

Airborne bistatic radar has long been recognised as offering advantages as a counter stealth and anti-jamming technology with respect to its monostatic counterpart. Algorithms for bistatic synthetic aperture image formation are now starting to appear in the open literature (Ref. 1). Given the potential of a non-monostatic configuration, bistatic and multistatic configurations may replace monostatic in some existing applications and inspire new ones. In any military radar system, a facility for robust automatic target recognition (ATR) system is desirable. The objective of the present project is to perform a limited study of the advantages, limitations and bottlenecks of ATR algorithms for bistatic configuration, and at the same time develop and test classification algorithms.

In this paper we present recent developments in the project, involving the application of principal component analysis (PCA) based classification algorithms in bistatic ATR. The database used for the validation of the algorithms is discussed, followed by a short note on PCA and why PCA is a suitable candidate in radar signal classification problems. Then the results from the experiments are presented followed by conclusions and a note on the future course of the project.

Database of airborne bistatic radar images (Ref.2)

Unlike the monostatic counterpart, in bistatic case, there are no datasets in public domain, which could be used in validation and analysis of any classification algorithm. As the next best alternative, an electro magnetic modelling tool (Ref.3) is used to model and generate a database for bistatic scenario.

In modelling the targets (military land vehicles), only the major (classifiable) features are modelled, ignoring the finer details. Based on this principle of modelling major features, four generic targets were simulated, viz. a battle field tank (MBT), an armoured personal carrier vehicle (APC), a stringer missile launching vehicle (STR) and a land missile launching platform (MSL).

In figure 1, the target models (not to scale) are illustrated and in figure 2, the corresponding synthetic aperture radar (SAR) images are shown. The SAR images are one of the realisations, with minimum bistatic angle. Figure 3 gives the SAR images of the targets with the addition of ground clutter and shadow.

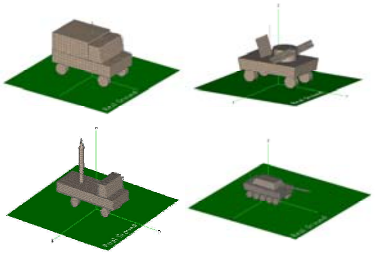

Fig.1 Models of the targets (APC, MBT, MSL, & STR in clockwise manner)

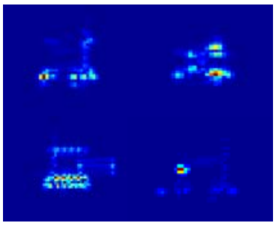

Fig.2 Bistatic SAR images of the targets (APC, MBT, MSL, & STR in clockwise manner)

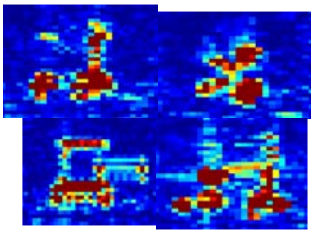

Fig.3 SAR images with ground clutter and shadow (APC, MBT, MSL & STR in clockwise manner)

PCA and its pertinence

Principal component analysis (PCA) has been used in data analysis and modelling and has a long and successful history. There has been some usage of PCA in SAR image classification in remote sensing and segmentation applications (Ref.4). But in the open literature, there has not been many reports on the usage of PCA for ATR.

The use of PCA for ATR has two justifications. First of all, PCA itself reduces the amount of data to be handled, and hence can reduce computational complexity. For a time-crucial application like ATR, this is a great advantage. Secondly, from our initial experiments with PCA and radar data, there was some evidence of a link between PCA and scattering centre model for radar data (Ref.5). The scattering centre model is a well-established model in radar community as of now. In addition to these, the results reported in this paper show that PCA-based classification approach is more robust with respect to the standard conditional Bayesian classification algorithms (Ref.6).

Experimental procedure

In the present work, the conditional Gaussian model based Bayesian classifier was taken as the standard - partly because of it closeness to the conventional Bayesian approach and partly due to the excellent results reported using this method for monostatic ATR (Ref.6). In this each pixel of the image clips, is assumed to be drawn from Gaussian distribution, conditioned on the target type and receiver azimuth[1].

$$r = s(\Theta, a) + w$$

where , r is the observed intensities of the pixels arranged in a one dimensional vector, and w is Gaussian noise and s is the complex signal conditioned upon Θ the receiver azimuth angle, and a the target type. The log-likelihood of an observed r, given $\{\Theta, a\}$ can be shown to be proportional to:

$$-\sum_{i=1}^{N}\left[\log(\Sigma_i)+\left(\frac{r_i - M_i}{\Sigma_i}\right)^2\right]$$

where r_i is the i^{th} pixel of the test-image-clip, Σ_i, M_i are the variance and mean of the pixel respectively (as estimated from the training data), and N is the total number of pixels in the test-image-clip. In this method, the recognition is done as per the Bayesian rule of maximising the probability

$$P(a \mid r) = P(r \mid a)P(a)$$

P(a), the probability of each type of vehicle was taken to be equal. In principal component analysis (PCA) (Ref.7,8), the image pixels are assumed to be the

[1]For monostatic case, its the target pose; but in bistatic case, receiver azimuth was deemed a more simple and convenient parameter

observed variables, depending upon the target type.

$$r = s(a) + w$$

The database is arranged so that all image clips collected at 10 degrees receiver elevation, are taken as training data. Each image clip in the training data-set, is from the same elevation but a different azimuth angle. Pixels of image clips are assumed to take different ***observations*** with changing azimuth angle. PCA is applied to the dataset to reduce the number of ***observed variables***. This is done in the following steps:

- For each image clip, the pixels are arranged into the observation vector, and consecutive image clips are taken as different observational values.
- All consecutive rearranged image-pixel vectors are stacked together to form the observation matrix.
- The observation matrix is normalized (to have unity variance), and all the observation vectors are zero centred. Let the final matrix be denoted by ***X.***
- From this observation matrix, the covariance matrix is found for the observation vector.

$$Q = X^H X$$

- Then the eigenvalue operation is applied on ***Q,*** to get the eigen vectors.
- Eigenvectors corresponding to ***k*** largest eigenvalues are stacked together to form matrix ***V***.
- Using this matrix ***V***, the training dataset is reduced in dimension to ***k***. The final output from the training phase are the database in reduced dimension and the converting matrix ***V***.
- In test phase, the test image clip is reduced in dimension using the converting matrix ***V***.
- Next the Euclidean distance is found from each point in the training database, and the class of target giving the least distance is decided as the class of the test clip.

Results

In figure 4, the results of classification algorithm performance for conditional Gaussian model based Bayesian (CGB) classifier has been displayed for both HH and VV polarised data. Figure 5 displays the results of classification algorithm performance for PCA based nearest neighbour classifier for both HH and VV polarised data.

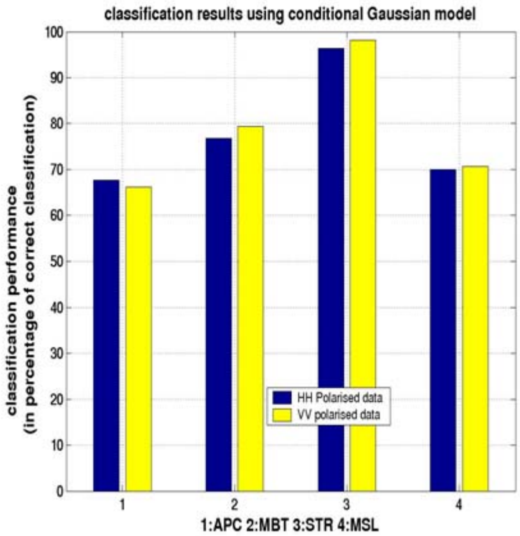

Fig.4 Bistatic ATR performance of conditional Gaussian model based classification algorithm

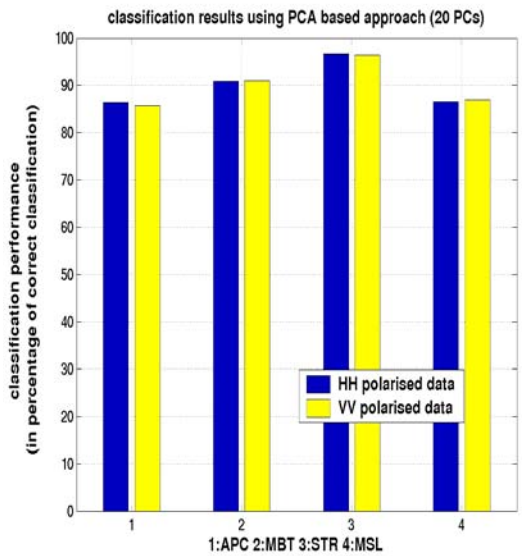

Fig.5 Bistatic ATR performance of PCA based classification algorithm

Conclusion and Discussion

Some observations drawn from the results are:

- Performance for both HH and VV polarisation are almost the same, for both the algorithms.
- Highest individual performance for CGB algorithm is around 97% for the target STR.
- Highest individual performance for PCA based algorithm is around 96% for the target STR.
- Lowest individual performance for CGB algorithm is around 66% for the target APC.
- Lowest individual performance for CGB algorithm is around 86% for the target STR.

Hence even though CGB algorithm can give very high performance for some targets, this performance is sensitive to the target type. PCA based algorithms may give slightly lower performance, than the CGB algorithm for the most classifiable target. But their performance does not vary so drastically with different targets. Hence it may be concluded that PCA based algorithms are more stable and robust.

Future Work

A limited study will be conducted to compare the results of ATR algorithms operating on both monostatic and bistatic data created synthetically. The objective is to quantify possible advantages and disadvantages of bistatic ATR. Further the use of polarimetric data in bistatic ATR will be addressed.

References

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