Ship Classification by Radar Range Profiles using the Maximum Likelihood Method

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Abstract: A general overview of feature-based classification via Bayes' theorem and the techniques that can be used to improve the performance of such a classifier are presented. The techniques utilised are the addition of a minimum likelihood, the addition of an ambiguity-reject (or unknown) class and the combination of the results obtained from several range profiles. The results obtained from Monte-Carlo runs of the classifier are compared with and without the implementation of these techniques to illustrate the improvement in performance. The features that contributed most to a correct classification result are found by applying the leave-one-out-method (LOOM).

1. Introduction

Radar range profiles can be used to help discriminate between different classes of ship. There has been much research in this area, with template matching [1], probabilistic techniques [2][3] and neural networks [4][5] all being proposed as valid classification methods.

This paper shows how the maximum likelihood method can be used to classify radar range profiles of ship targets. Such Bayesian-based classifiers are often chosen in preference to other classification schemes as they theoretically yield the smallest probability of mis-classification [6]. The classifier is feature-based and combines the conditional probability densities associated with the feature-values that characterise a particular range profile.

2. The Dataset

The dataset used to test the classifier was recorded using a cliff-top radar with a bandwidth of 50MHz and spatial resolution of 3m. It contains the profiles of 11 ships that circled in front of the radar in order to collect profiles from a range of aspect angles. The radar collected two sets of profiles; one set for training the classifier and the other for testing the classifier. The two sets were collected at different times on the same day. The profiles were integrated to improve the signal to noise ratio, with each being the sum of 250 single-pulse range profiles.

3. Architecture

The chosen features are combined using Bayes' theorem to calculate the probability of a range profile being a member of a particular class of ship based on all of the available features. This probability is calculated using *Equation 1* below.

$$P(w_i \mid \mathbf{X}_j) = \frac{P_i \prod_{j=1}^{n} p_i(\mathbf{X}_j)}{\sum_{i=1}^{L} P_i \prod_{j=1}^{n} p_i(\mathbf{X}_j)}$$

Equation 1 - Bayes Theorem

Here, $P(w_i|X_j)$ is the probability of the range profile being of class w_i based on X_j, where X_j is the vector of feature-values. P_i is the *a priori* probability, $p_i(X_j)$ is the multivariate class conditional density function (CDF), L is the number of classes known to the classifier and n is the number of features. In this case all of the classes are equally likely and so their respective *a priori* probabilities have identical values.

After the calculation of the probability, discrimination between classes is performed, with each range profile being assigned to the class that yields the largest probability. It has been shown previously [1][2][8] that performance can be improved by using the techniques described in the following sub-sections.

3.1 Minimum Likelihood

There is a possibility that a measurement associated with a feature is not plausible in comparison with the information provided by the other features. Such a measurement would yield an extremely low probability for that class, as a consequence of the probability being calculated by multiplying together the conditional probabilities generated for each feature. A solution is to have a minimum likelihood associated with the conditional probabilities that are below a threshold. This would still yield a low conditional probability for a particular feature measurement, but its knock-on effect would not be so detrimental to classification performance. Therefore, the minimum likelihood is used to soften the effect of these statistical outliers.

3.2 Ambiguity Reject

The addition of an unknown class can help to improve the performance in cases where the final classification decision is ambiguous [9][10]. For example, the probabilities for two classes may be very similar and it may be sensible to reject the decision and assign the test range profile to an unknown class.

3.2 Combining Results

In some classification schemes, a single profile has been used to make a classification. However, there is a possibility that a single test profile may not always show a good match with its correct class. By firstly combining the results of several profiles before applying Bayes' theorem the affect of such a profile may be alleviated as other test profiles are - in general - likely to be representative of the correct class.

4. Simulation

Each class is described by a set of CDFs representative of a set of features that will be used in the discrimination process. The performance of such a classifier is therefore dependent on the 'utility' of the CDFs chosen to represent the range profiles.

As the characteristics of a range profile are dependent on the aspect angle it is viewed at, the training range profiles associated with a particular class are divided up into aspect bins. An improvement in the performance of the classifier using aspect angle bins has been shown [8]. For each bin a set of CDFs is generated to describe the features of the profiles in that particular bin. A database is then developed containing all of the CDFs needed to describe a class of ship observed in any aspect angle bin.

The classification algorithm follows a process summarised by the following steps. Firstly, a test profile is chosen randomly from a database of test profiles. The aspect angle of this profile is then checked to see if it is sufficiently far from broadside – this is because range profiles close to broadside contain little discriminatory information. The feature-values describing the characteristics of this profile are then calculated. These feature-values are input to the CDFs - relating to the appropriate aspect bin - to calculate the conditional probability of the feature-value being recorded from each class of ship. Finally, these conditional probabilities are combined using Bayes' theorem via *Equation 1* to calculate the probability of the test profile being a derivative of each class of ship. The following features were chosen to describe each profile:

a) The number of peaks above a certain threshold,

b) The percentage of the profile which is above its mean value,

c) Its maximum value after normalisation,

d) The position of its maximum value,

e) Its standard deviation,

f) Its length.

5. Utility

To test which features contributed the most to the correct classification of range profiles, Monte-Carlo runs were performed using different combinations of features via the LOOM. The better a feature is at discriminating between different classes the greater the drop in performance will ensue from it being unavailable to the classifier. This method helps to gain an understanding of which kind of features should be utilised in the final classification decision.

6. Results

Performing Monte-Carlo runs assessed the performance of the classifier. Each run consisted of 10000 independent trials that each combined a certain number of profiles before making a classification decision. A control Monte-Carlo run was performed on the classifier followed by runs that tested the proposed improvement techniques. Results were gained using a large number of different values for the minimum likelihood and the number of profiles used. A small subset of these results is shown in *Table 1*. A test range profile was assigned to an unknown class if the ratio of the two greatest probabilities was less than 1.25.

Trial	Minimum Likelihood	Number of Combined Results	Unknown Class	Increase in Percentage Correct Classification
1	0.1	1	No	26.25
2	0.000001	1	No	33.75
3	0.000001	1	Yes	35.14
4	0.000001	10	Yes	69.63

Table 1 – a comparison of the different improvement techniques.

Trials 1 and 2 show the improvement in the correct classification of range profiles caused by applying a minimum likelihood and the sensitivity of the results to what particular minimum likelihood is chosen. Performance increases as the minimum likelihood decreases in trial 2 as more of the discriminatory aspects of each CDF are revealed. However, if this minimum likelihood is set too low the effect of statistical outliers leads to a drop in the performance. Trials 2 and 3 show the improvement resulting from the addition of an unknown class for the reason discussed previously. Finally, trials 3 and 4 show how the combination of the results of several profiles leads to a further improvement owing to there being more information available upon which the classification decision is made.

The results of Monte-Carlo runs where a particular feature has been omitted from the final calculation of the probability of a profile belonging to each class are shown below in *Figure 1*. A minimum likelihood of 0.000001 and the combination of the results of 20 profiles were used to generate these results.

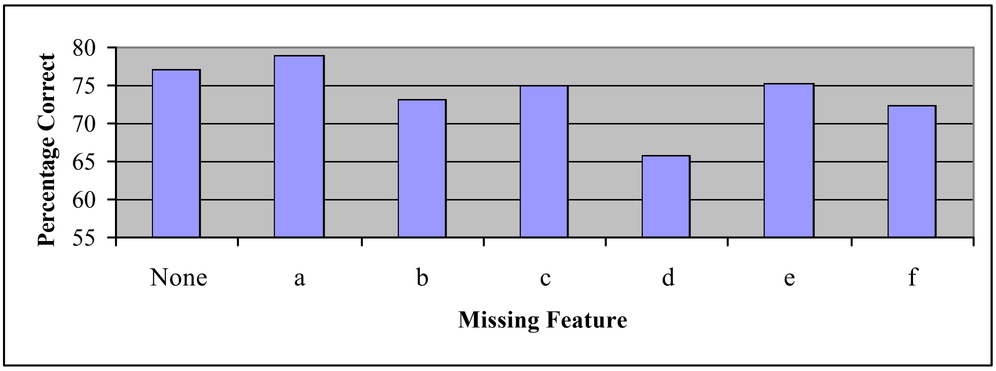

Figure 1 - a comparison of the performance of the classifier for different sets of features.

The results in Figure 1 show that the feature relating to the number of peaks above a threshold was the only feature that did not contribute to the correct classification of range profiles. The feature that contributed most was the position of the maximum value, which led to a greater drop in performance than the feature relating to the magnitude of this value. This indicates that the positions of the peaks in a profile are more important than their respective magnitudes and that the classifier should use more features that relate to these positions. Figure 1 shows that the performance of the classifier can be improved by applying the LOOM to reject inappropriate features.

7. Summary and Conclusions

All of the techniques described above led to an increase in the performance of the classifier. In particular, the combination of the conditional probabilities of several profiles led to a marked increase in the correct classification of range profiles.

Most of the proposed features contributed to the correct classification of range profiles. It is likely that there are many other features that can be derived from a range profile, and more research needs to be done to find the best combination. To improve the performance, a weight could be applied to each feature, with those which showed a greater contribution after applying the LOOM being assigned more weight in the classification decision.

8. References

[1] Tough R. J. and Ward K. D. ‘Report on a study of Range Profile Classification’, TW Research Limited, March 1996.

[2] Ballard J. P. ‘A Maximum Likelihood Range Profile Classifier for Maritime Targets’, AGARD Non-co-operative Air Target Identification Radar Symposium, Mannheim Germany, April 1998.

[3] Webb A. R. ‘Gamma Mixture Models for Target Recognition’, Pattern Recognition 30 (12) (2000), pp2045-2054.

[4] Luttrell S. P. ‘Using Self-organising Maps to Classify Radar Range Profiles’, IEE Artificial Neural Networks Conference, pp335-340, 1995

[5] Inggs M. R. and Mitchell A. D., ‘Ship Target Recognition using Low Resolution Radar and Neural Networks’, IEEE Trans. Aerospace & Electronic Systems, Vol 35, No. 2, pp. 386-392, 1999.

[6] Fukanaga K, ‘Introduction to Statistical Pattern Recognition’, Academic Press, 1990.

[7] Freund J E, ‘Mathematical Statistics’, Prentice Hall, 1992.

[8] Leonard T. P. ‘A Ship Range Profile Classifier based on the Wavelet Transform’, DGON International Radar Symposium 98, Munich Germany, Sept. 1998.

[9] Chow C. K. ‘An Optimum Character Recognition System Using Decision Functions’, IRE Trans., Electronic Computers, Vol EC-6, pp. 247-254, Dec. 1957.

[10] Fumera G., Roli F. and Giacinto G. ‘Reject Option with Multiple Thresholds’, Pattern Recognition, 30 (12) (2000) pp2099-2101.

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