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Electronic Warfare: Issues and Challenges for Emitter Classification

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ABSTRACT

Electronic warfare (EW) is an important capability that provides advantage to defence forces over their adversaries. Defence forces gather tactical intelligence through EW sensors, which provide the means to counter hostile actions of enemy forces. Functions of an EW system is threat detection and the area surveillance so as to determine the identity of surrounding emitters. Emitter classification system identifies possible threats by analysing intercepted signals. Problem of identifying emitters based on its intercepted signal characteristics is a challenging problem in electronic warfare studies. Major issues and challenges for emitter classification such as drifting of emitter parameters due to aging, operational characteristic of an emitter, i.e., same emitter can operate on multiple bands and multiple pulse repetition frequencies (PRFs) are highlighted. A novel approach based on some well-known statistical methods, e.g., regression analysis, hypothesis testing, and discriminent analysis is proposed. The effectiveness of the proposed approach has been tested over ELINT (Electronic Intelligence) data and illustrated using simulation data. The proposed approach can play a solution for wide variety of problems in emitter classification in electronic warfare studies.

Keywords: Electronic warfare, emitter classification, radar drift analysis, discriminent analysis, regression analysis

1. INTRODUCTION

In electronic warfare (EW)[2], emitter identification[1,4-5,7-13,15,18] is a necessary requirement to apply countermeasures against threat emitters. Electronic support measure (ESM)[3,16] receivers play an important role by intercepting signals and measuring their physical parameters. In most of the cases, ESM systems are unable to recognise the different emitters of the same type or class. Radar emitter identification based on a collection of received radar signals is a subject of wide interest in defence applications. The received signals usually consist of sequences of pulses emitted from multiple radar transmitters. If different radars transmit pulses with different frequencies or pulse repetition frequencies (PRFs), then it is not difficult to distinguish one from another. However, in modern radar systems, the same emitter can operate in multiple bands and multiple PRF. To classify emitters in such an environment is a challenging task[7,10].

Ford[7], *et. al.* has proposed a knowledge-based system for emitter classification and ambiguity resolution. They have described a three-step process for standard emitter classification. In the first step, the intercepted record is compared to the entries in a mission-specific library file. Entries in the mission-specific library represent emitter modes that are known to be operational at a specific location. If there is no match in the file, then intercept is compared to the entries in the emitter mode file (EMF) which is a library of emitters of a particular nomenclature. Finally, the third step in the emitter identification process is the functional classification file (FCF). Unlike the other two files, the FCF identifies only the suspected function of the emitter. The FCF always returns an indication as the function of the emitter. Thus, FCF insures that every intercept that is processed is identified. We have similar kind of study but instead of matching in the three-step process, only matching with emitter database is required. Hassan[8], introduced a method for evaluating the quality of the deinterleaved radar cells by applying a new approach of performing the deinterleaving of radar pulses and identifying their corresponding radars into one step. By applying the proposed method, the high quality deinterleaved cells can be only submitted to the threat library of the EW system to identify their corresponding radars. Dorwin[5], *et al.* describe a Dempster-Shafer technique that exploits a set of hierarchical parameter trees to provide a detailed description of signal behaviour. This technique provides a significant reduction in ambiguity, particularly for agile emitters whose signals provide much information for the algorithm to utilise. Anjaneyulu[1], *et. al.* present a radar emitter identification and classification technique based on Fuzzy ART and ARTMAP neural networks.

The signal parameters[17] considered for emitter classification are frequency, pulse repetition frequency (PRF), pulse width (PW), and antenna scan period (ASP)[1,16]. Sometimes, emitters operate in different frequency bands and multiple PRFs, this will make the identification problem very difficult.

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Another problem is the drifting in the emitter parameters as time progress. The present study addresses some of the classical methods[14] in this context. The problem can be divided into three aspects; first one is to detect whether the incoming record belongs to one of the existing classes in the database or it is a new class. Once the record is found to belong to an existing class, next problem is to find the closest match with the existing class. Third problem is to study the drifting in the emitter parameters and develop a suitable classification based on this. In the present study, the authors started with some statistical approaches[6,14] to these problems. Statistical characteristics of the emitter parameters in all classes are captured and a confidence bound is calculated for parameters in each class. When the new set of parameters is lying outside the confidence bound of all the existing classes, then it is considered as a new emitter record. When the new set of data belongs to one of the existing classes, then discriminent analysis is applied to find the closest match.

2. ISSUES AND CHALLENGES FOR EMITTER CLASSIFICATION

Many problems have been noticed to classify emitters correctly for current EW study. The problems and related challenges have been described in this section to highlight the need of catering such issues prior to applying any classification method. Some of the problems, which were encountered during the current study, are given below.

The first issue arises due to the addition of new sensors in EW systems. The classification of intercepted signal from newly added sensor is a difficult task. Most of the existing approaches are unable to distinguish whether intercepted records belong to an existing emitter or it is a new one. In this paper, hypothesis testing and confidence interval-based approaches have been introduced to address the above-mentioned problem.

It is also observed that a single emitter can have several modes of operation. A new mode is achieved by shifting the range of one or more parameters by some factor. For example, an emitter with 550 as PRF value can operate on multiple PRF values which are some multiple factors of 550, i.e., 1100 or 2200 etc. It leads to the ambiguity in identifying emitter due to the overlapping decision boundaries among the existing emitters. Ambiguity is a huge problem in EW. Ambiguity exists among many different areas of the signal environment. The ambiguity problem is getting worse as time goes on as new emitters are introduced. The three parameters, which have traditionally been used to classify emitters, generally produce ambiguous results. The conventional approach to ambiguity resolution is by adding new parameters for comparison but it is time-consuming, and can be performed by experienced EW analysts only.

Another approach is by assigning the ambiguous area to the emitter with the highest priority. This approach is required into the EW system prior to a mission. The priorities are subjective in nature and difficult to be assigned. Ford[7], *et al.* has introduced knowledge-based approach for ambiguity resolution, but again, building a knowledge base is very difficult in most of the EW scenarios. This paper introduces scaling of multiple modes and band-wise classification approach to overcome this challenge.

For a particular emitter class, some observations are significantly different from other parameter values. These observations can be treated as outliers. Presence of outliers in the emitter signal database also affects the classification accuracy. Outliers are not uncommon for emitter classification tasks. Identification of outlier is a challenging problem in data analysis. Therefore, two basic approaches of outlier detection are also applied as a data pre-processing step in the proposed approach.

It is observed that emitter shows some drift in its parameters as time progresses. Here, the problem is to identify the underlying pattern in the parameter drift and classify the emitter according to it. No study was found in the current literature to solve the problem of drifting in emitter parameters. Regression analysis[6,14,18] based approach for radar drift analysis has also been introduced.

3. PROPOSED APPROACH

A novel approach for solving various problems of emitter classification is proposed. The proposed approach is a combination of various statistical methods which are applied and modified to meet the requirement. The proposed approach comprises three components i.e. data pre-processing, emitter classification, and radar drift analysis.

3.1 Data Pre-processing

Data pre-processing is a prerequisite for any kind of data analysis activity. The classification accuracy depends upon the quality of the data. Data pre-processing provides the desired input format for classification algorithms. It also removes outliers and undesired parameters. Since an emitter can operate in several operational modes, therefore scaling of multiple modes PRF method is also presented. The current study also applies two popular outlier detection methods for catering to the abnormal observations.

3.1.1 Scaling for Multiple Modes

It is observed that emitters can operate on multiple modes, i.e., same emitter can operate on multiple bands and multiple pulse repetition frequencies (PRFs). For example, an emitter with x as PRF value can operate on multiple PRF values which are some multiple factor of x, i.e., $2x$, $3x$, etc. A unique approach of scaling multiple PRF has been employed prior to emitter classification.

For every emitter class, minimum PRF is chosen to scale the effect of multiple modes PRF. The information about the presence of multiple factor for a particular class was gathered. A history of all emitters along with their multi-mode operation was created. Whenever, a new intercept was observed then multiple factors of PRF for every emitter were computed. PRF of the intercepted record was scaled down by that multiple factor for an individual emitter class. This approach is helpful for analysing intercepted records in several modes.

Similarly, an emitter can operate on multiple bands, i.e., same emitter can operate on E and F bands. Due to this problem, high variance in frequency was observed. To overcome such a problem, an emitter class was further subdivided wrt band of operation. It means that if an emitter X operates on two bands E and F, then two class labels for that emitters $X : E$ and $X : F$ are introduced.

3.1.2 Outlier Detection

Outlier[6] is defined as an observation that lies at an abnormal distance from other values in a random sample from a population. Outliers are often referred to as unusual observations that are far from the mass of data. ELINT data set always contains outlying observations. For a particular emitter class, some observations are significantly different from other parameter values. These observations can be treated as outliers. Identification of an outlier is a challenging problem in data analysis. Two classical procedures were adopted for outlier detection.

Two graphical techniques for identifying outliers are scatter plots and box plots. The box plot is a useful graphical display for describing the behaviour of the data in the middle as well as at the ends of the distributions. The box plot uses the median and the lower and upper quartiles (defined as the 25th and 75th percentiles). If the lower quartile is Q1 and the upper quartile is Q2, then the difference (Q2-Q1) is called the inter-quartile range or IQ. A box plot is constructed by drawing a box between the upper and lower quartiles with a solid line drawn across the box to locate the median. The following quantities (called fences) are needed for identifying extreme values in the tails of the distribution:

(a) lower inner fence: Q1 – 1.5*IQ
(b) upper inner fence: Q2 + 1.5*IQ
(c) lower outer fence: Q1 – 3*IQ
(d) upper outer fence: Q2 + 3*IQ

A point beyond an inner fence on either side is considered a mild outlier. A point beyond an outer fence is considered an extreme outlier. Another popular method of detection outlier is the three-sigma detection, the mean (M) and standard deviation (SD) of the observations were calculated and limits were determined as follows,

(a) Lower limit: M –3*SD
(b) Upper limit: M + 3*SD.

The observation that lies outside these limits is treated as an outlier.

3.2 Emitter Classification

Emitter classification[1,4-5,7-13,15,18] is the process of assigning a new record to one of the existing classes. When the new set of observations does not belong to the existing class, it has to be treated as a new class. Emitter classification plays a crucial role in EW study. Later problem can be solved using statistical hypothesis testing[14] or confidence interval method[14]. Once the new set of parameters belongs to the existing class, one has to find the closest match. Discriminent analysis[14] is a statistical classification procedure for identifying the closest match. The proposed approach of emitter classification is a combination of two well-known statistical methods, i.e., hypothesis testing and discriminent analysis. For the current study, many classification methods have been analysed but most of these are not suitable for classifying emitters in EW environment due to large number of emitter classes.

3.2.1 Hypothesis Testing Approach

In practice there is lack of knowledge about the possible classes. In this situation one has to test whether the individual belongs to the existing class or a new class. The solution to this problem is described below. In the present study, it was assumed that the emitter parameters follow multivariate Gaussian distribution. Let H_0be the null hypothesis that an individual with measurement U come from $N_p(\mu_i,\Sigma), i=1,2,...,q$, where q is the total number of emitter classes present in the emitter database, $\mu_i$is the mean vector corresponds to the i^{th} class and Σ is the covariance matrix. From the normality assumptions one has the statistics

$$d_i = (U-\mu_i)'\Sigma^{-1}(U-\mu_i) \sim \chi^2_p$$

For testing the belongingness of individual measurements in one of the existing classes in the database, a chi-square test criterion with significance level α=0.05 was proposed. If $d_i > \chi^2_{\alpha,p}$ for all emitter classes in the database, it was concluded that the individual measurement U belongs to a new emitter class.

3.2.2 Confidence Interval Approach

Another way to address this problem is based on the confidence limit of the emitter parameters. The statistical characteristics, such as mean and variance of the parameters of each class were calculated. Suppose there are q classes C_i=i=1,2,...,q, the estimated mean and standard deviation of the j^{th} parameter of the i^{th} class C_i is given by (m_{ij}, s_{ij}). Similarly, one can calculate 95 per cent confidence interval of the j^{th} parameters of i^{th} class C_i as $[m_{ij}-t_{\alpha/2}s_{ij}, m_{ij}+t_{\alpha/2}s_{ij}]$, where $t_{\alpha/2,n-1}\{\ \}$ is the Students t table value at n–1 degrees of freedom. If the new set of parameter values belongs to one of the confidence intervals, it can be considered to belong to an existing class, otherwise, it would be treated as a new entry.

3.2.3 Discriminent Score Approach

The problem of classification, is about deciding the membership of an observed individual to one of a given set of population to which it can belong. Discriminant analysis identifies the closest association of the observed records in to one of the existing classes in the database.

Let us consider 'n' class and in each class calculate mean Vector $M=(m_1,...,m_n)$ and covariance matrix,

$$\Sigma = \begin{pmatrix} \sigma_{11} & \cdots & \sigma_{1n} \\ \vdots & \ddots & \vdots \\ \sigma_{n1} & \cdots & \sigma_{nn} \end{pmatrix}.$$

Give a set of measurement ($A_1, A_2, \ldots A_n$) for any individual, k discriminent score (S_i) can be calculated using Eqn. (1),

$$S_i = l_1 A_1 + l_2 A_2 + \ldots + l_n A_n - \frac{1}{2}(l_1 m_1 + l_2 m_2 + \ldots + l_n m_n) + \log \pi_i, \quad i = 1,2,3,\ldots,k \qquad (1)$$

Let $\sigma^{i,j}$ be the (i, j)$^{\text{th}}$ element of Σ^{-1}, then $l_j = \sigma^{j1} m_1 + \sigma^{j2} m_2 + \ldots + \sigma^{jn} m_n, j = 1,2,3\ldots,n$ and π_i be the prior probability can be taken as

$$\pi_i = \frac{n_i}{\sum_{j=1}^{k} n_j}, i = 1,2,3\ldots,k$$

The new individual is assigned to the group for which the score is the highest. This procedure minimises the loss (or frequency of wrong identification) in long run.

3.3 Radar Drift Analysis

Emitters show some drifting in its parameters as time progresses. One needs to capture this problem before developing a classifier. A regression method helps one to capture the driftness in emitter parameters.

3.3.1 Regression-based Classification for Drifting in Emitter Parameters

Emitter parameters (Frequency, PRF, and PW) show some drift in their parameters as time progresses. Here, the problem is to identify the underlying pattern in the parameter drift and classify the emitter according to it. The problem can be formulated as follows

The parameter vector of emitter at different time point is considered as

$$Y_t = [y_{1t}, y_{2t}, \ldots, y_{kt}],\ t = t_1, t_2, \ldots, t_n$$

The drift can be modelled as

$$Y_t = g(\beta, t) + \varepsilon_t, t = t_1, t_2, \ldots, t_n \qquad (2)$$

From a given set of observation $\{y_{ti}\}$, first one has to identify the function g and then estimate the unknown quantity b out of it. This is the problem of regression analysis. Next the problem of emitter classification is addressed. The error sequence $\{e_t\}$ is assumed to follow normal distribution and constant variance. The regression model is fitted to all the existing classes of emitters. Suppose there are q classes $C_i, i = 1,2,\ldots,q$, the fitted model in the i^{th} class C_i is given by $\hat{Y}_{t,C_i} = g_{C_i}(\hat{\beta}, t),\ t = t_1, t_2, \ldots, t_n$ .Similarly, one can predict the future value at a new time point time t_k as $\hat{Y}_{t_k,C_i}$ and corresponding 100(1–a) per cent prediction interval as $\left[\hat{Y}_{t_k,C_i} - t_{\alpha/2}\sigma_{\hat{Y}}, \hat{Y}_{t_k,C_i} + t_{\alpha/2,n-2}\sigma_{\hat{Y}}\right]$, where $t_{\alpha/2,n-2}$ and $\sigma_{\hat{Y}}$ are the Students't' table value at $n-2$ $d.f$ and standard error estimate of $\hat{Y}_{t_k,C_i}$ respectively. If the new set of parameter values belongs to one of the confidence intervals, it can be assigned an existing class otherwise it is treated as a new entry.

Emitter parameters (Frequency, PRF, and PW) show some drift in their values as time progresses. Here, the problem is to capture the underlying pattern in the parameter drift and classify the emitter according to it. Radar drift plots fit a curve based on each parameter and predict the confidence interval for the new parameters according to

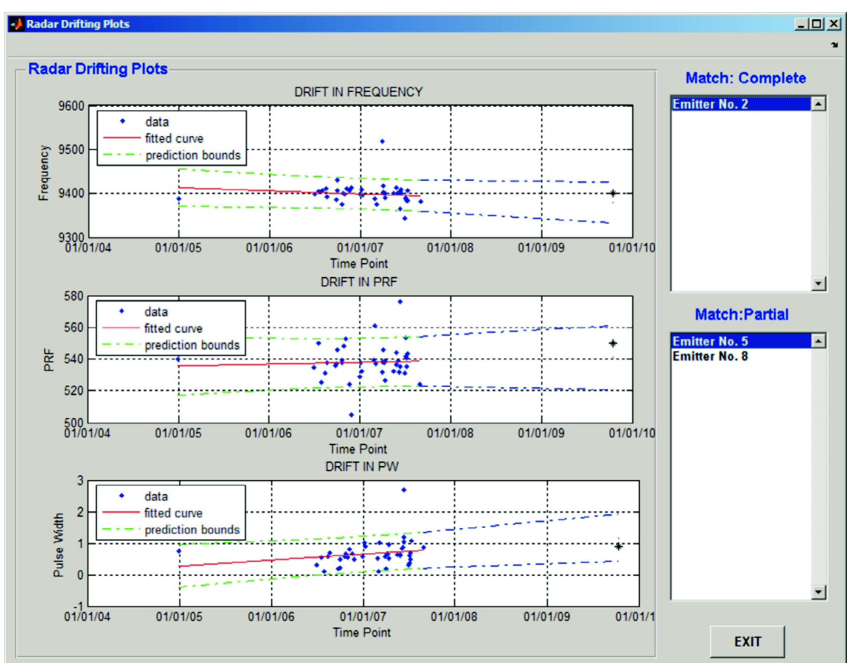

Figure 1. Radar drifting plots.

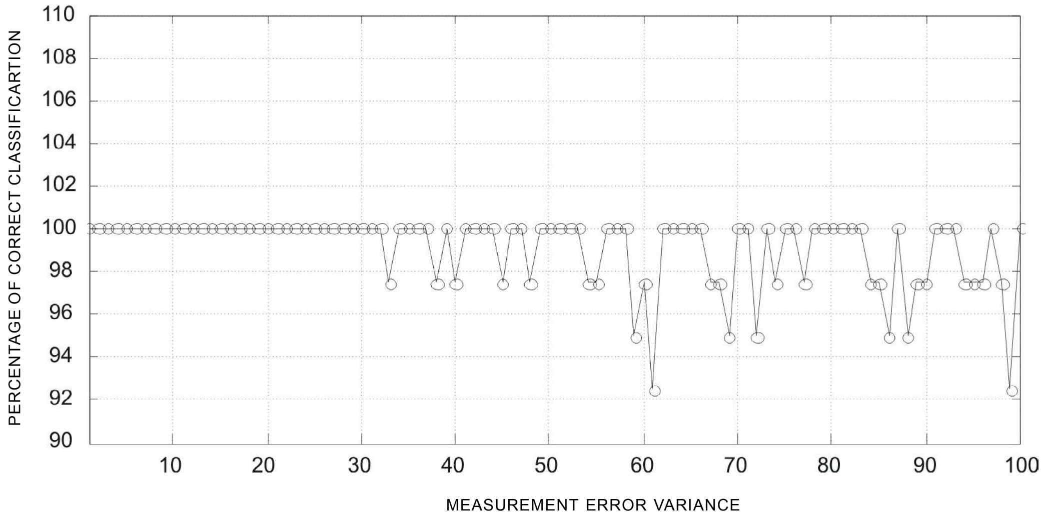

Figure 2. Classification accuracy using discriminent analysis.

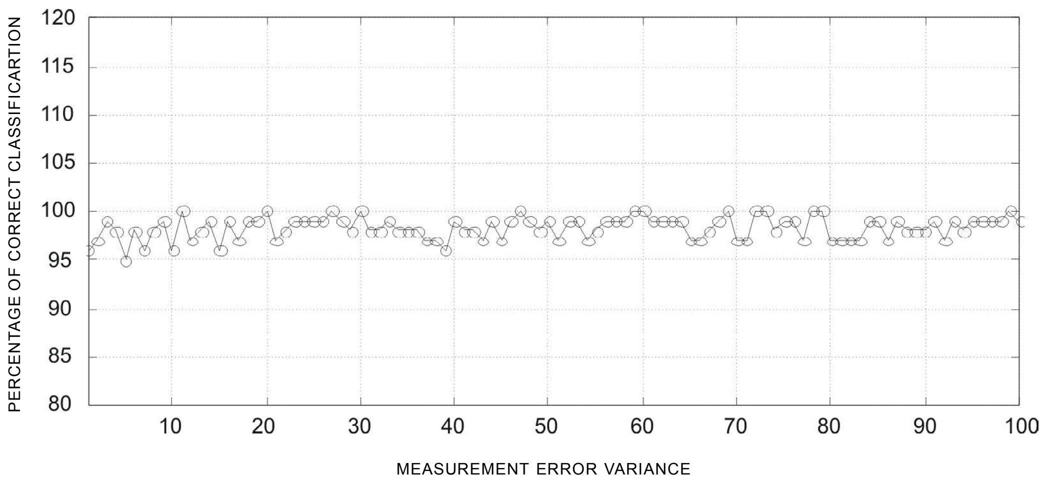

Figure 3. Classification accuracy using regression analysis.

their statistical characteristics. Figure 1 illustrates the radar drift analysis and emitter classification method. Data points are plotted wrt the observed time points.

Blue dots, red lines, and green lines represent parameter values, fitter curve and confidence limit, respectively. Blue dotline indicates the confidence limit of the new parameter value at a future time point and black dot represent the parameter value at that time. If observed parameter values that correspond to frequency, PRF and PW are inside the confidence limit, the corresponding class is displayed in the match: complete box. If there is some partial match in the parameters, it is displayed in the Match: Partial box.

3.3.2 Limitation

The performance of the method is mainly dependent on the number of samples. An emitter should have latest three records in the database to generate confidence interval. Therefore, emitters with less than three records cannot be considered for radar drift analysis. The classification accuracy for emitters, which are having less number of samples, is not satisfactory.

4. SIMULATION RESULTS

In the simulation study, the authors synthetically generated the emitter parameter data with some observation error. Observation error was generated through normal random numbers. Parameters of the observation error distribution were decided form the real data under all possible conditions. Figure 2 illustrates this analysis results. Figure 2 shows the classification accuracy using discriminent analysis on simulation data.

A similar study, has also been carried out in radar drift analysis also. Here, the authors considered a linear drift in the parameters and the values were simulated with some observation error. Choice of this model and distribution parameters were based on the ELINT data analysis. The results are displayed in Fig. 3.

The simulation study shows that the algorithms, which have been used to study the ELINT data analysis, performed well in all possible situations.

5. CONCLUSIONS

In this paper, major issues for emitter classification like drifting of emitter parameters due to aging, operational characteristic of emitter, etc, have been discussed. The paper also proposes a solution framework based on regression analysis, hypothesis testing and discriminent analysis to overcome the challenges for emitter classification. Regression analysis has been applied for capturing drifting in the emitter parameters. Hypothesis testing has been used to detect the belongingness of the intercepting record in the database. Once the record belongs to an existing class, then discriminent analysis is applied to classify emitter to the closest match within the existing class. It was observed that intercepting signal cannot be directly used as inputs to the above-mentioned analysis due to operational characteristics of various emitters. Therefore, a novel approach for scaling multiple PRFs and outlier detection has been introduced in the paper. The effectiveness of the proposed approach has been tested over ELINT (Electronic Intelligence) data and illustrated using simulation data. An interactive adaptive interface has also been developed for carrying out data analysis and pattern recognition for EW environment. The successful implementation of the proposed approach depicts the utility of the approach. The developed interface can be integrated with latest visualisation techniques, such as geographical information system for enhancing the understanding of the results and patterns. The proposed approach can be useful to overcome the challenges of emitter classification in EW/ESM systems.

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