Analysis of Measured Radar Data for Specific Emitter Identification

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***Abstract*—Measured radar data assisted in the successful development and implementation of Specific Emitter Identification (SEI) signal processing algorithms. The aim of the algorithm is the identification of a specific emitter within a single class of emitters. The processes developed are pulse extraction, feature calculation, dimensionality reduction and classification. A pulse is detected whenever the phase changes from being random to being linear. Time domain features are then calculated from these extracted pulses to populate a feature vector. Some redundancy exists in the feature vector and a process of dimensionality reduction is followed to obtain the optimum set of features. A Fuzzy ARTMAP classifier completes the process of specific emitter identification to demonstrate the improvement in Correct Classification Decisions (CCD) using the reduced feature vector.**

I. Introduction

Electronic Support (ES) within the context of Electronic Warfare (EW) is concerned with the detection, interception, location, analysis and identification of radiated electromagnetic energy. The information obtained from real-time surveillance enables situational awareness, threat avoidance and the deployment of countermeasures.

The research presented in this paper applies to the field of ES. Measurement trials were conducted to acquire the data required for the development of Specific Emitter Identification (SEI) algorithms. These algorithms can be used in various applications such as network security and military situations [1], [2].

The successful implementation of these SEI algorithms depends on the thorough analysis of measured data. The first stage in the data analysis is to detect pulses within the measured data. Pulses with Signal-to-Noise Ratios (SNR) sufficient for processing are detected and extracted from the measured data. Determining features from pulses requires high SNR because SEI is interested in subtle differences between nominally identical signals. Using only the data from the extracted pulses, specific characteristics can be observed and associated with the relevant radar system. The numerical values attributed to each of these characteristics are referred to as features. These features are combined in a feature vector, and the optimum set of features is then used in the classification process.

II. Measurement Data

A. A. *Measurement Setup*

Three of the same radar systems were measured so that different transmitters with exactly the same design specifications can be analyzed for SEI. Even though the transmitters belong to the same kind of radar, they may exhibit subtle differences in their transmitted pulses.

The measurement setup used during the trials is shown in Fig. 1. A Digital Receiver (DRx) was used as the main data recorder. The radar transmitters that were measured operate outside the DRx frequency band. A mixer was therefore required to mix the pulse frequency into the DRx frequency band. A spectrum analyzer also formed part of the measurement setup to determine the carrier frequency of transmitted pulses.

The receiver antenna was 1 km away from the transmitting radar. The signals were recorded in an environment that contained noise from different signal sources, including thermal noise. Only those pulses with SNR above 30 dB were used for signal processing. The SNR was calculated using estimates of pulse power and noise power.

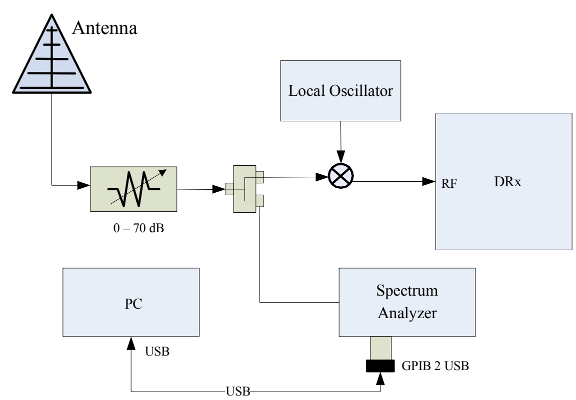

Figure 1. Setup for radar signal measurements

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III. Analysis of Measured Data

The raw measured data are used for analysis. During the data analysis process, the following algorithms were developed and implemented: pulse detection, feature extraction, dimensionality reduction and classification. Fig. 2 shows the process by which the recorded data are reduced to a single output, namely the identification result.

A. Pulse Detection

In the time domain, the start of a pulse can be detected using amplitude or phase data. Amplitude data are more susceptible to noise and would therefore not give the most accurate results. Phase data, on the other hand, are more robust against noise and can be used more efficiently to determine the exact times when a pulse starts and ends [3]. Other statistical methods are also available, as mentioned below.

To determine the start of a signal, [4] and [5] used a variance fractal dimension measure together with a Bayesian step change detector. Temporal, nonstationary signals' fractal dimensions change over time. Multifractals can be used with such signals, e.g. radar pulses that have time-varying fractal dimensions [4], [6] and [7]. A major advantage of using multifractal analysis is the normalizing effect that fractal dimensions have on signals (fractal dimensions always have values between 1 and 2).

A robust and simple solution to detect the start of a transmitted pulse is proposed in [3]. As mentioned earlier, the phase of a signal is less susceptible to noise than the amplitude of the signal. Furthermore, the slope of the phase associated with the pulse displays linear properties. By exploiting this property, the start and end time of the pulse can be accurately separated from the noise. This method of signal extraction has proved to be accurate and less complicated than fractal dimensions and was used as the pulse detector.

B. Feature Calculation

Features are extracted from the pulses using mainly time domain characteristics [8], [9]. The instantaneous amplitude, phase and frequency components are calculated using (1) to (3) [10], [11].

$$a(t) = \sqrt{i^2(t) + q^2(t)} \text{ in [V]} \tag{1}$$

$$\theta(t) = \tan^{-1}\frac{q(t)}{i(t)} \text{ in [rad]} \tag{2}$$

$$f(t) = \frac{1}{2\pi} \times \frac{\Delta\theta(t)}{\Delta t} \text{ in [Hz],} \tag{3}$$

with $i(t)$ and $q(t)$ the in-phase and quadrature components of the complex valued samples of the extracted pulse.

A total of eighteen features are calculated from the instantaneous amplitude, phase and frequency. During the feature calculation, a single numerical value is determined for each feature and entered into a vector to be used during classification.

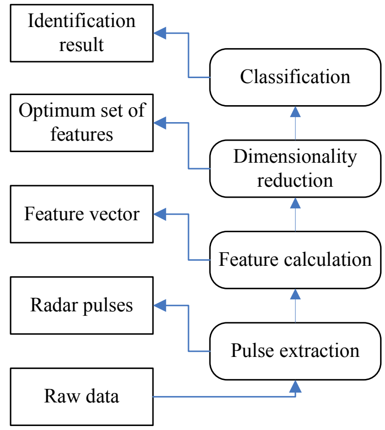

Figure 2. Specific emitter identification process

C. Dimensionality reduction

The problem of identifying a specific (or unique) radar system out of a collection of three radars initially required the input of eighteen features into the classification system. The classification system has a single output dimension as it is only concerned with classification decisions of one out of a possible three similar radar systems.

For any classifier, the addition of more features in both the input and the output space increases the classification accuracy up to a certain point. Beyond this point classification performance is reduced when additional features are added. This phenomenon is widely known as the *curse of dimensionality* [12], [13]. As some of the input features in this particular problem are correlated with each other, this set of features has an intrinsic dimensionality. This means that the input data from a subspace of lower dimension can describe the radar data just as well as the original eighteen input features. Furthermore, there is a strong demand for more data points to be able to train a classifier adequately. For example, if we require M input data points in eighteen dimensions (d = 18) to properly train the classifier, the input dataset would comprise of M^{18} values. It is clear that the amount of data required for classification quickly grows and renders the classification solution impractical.

Thus in order to explore the intrinsic dimensionality and possibly reduce the large amount of data of the original eighteen input features, a dimensionality reduction step is added before classification. Only a selected subset of the original set will be used to train and evaluate the classifier. Here one of four possible pre-processing techniques can be applied, i.e. mutual information, correlation method, Linear Discriminant Analysis (LDA) or the gamma test.

D. Classification

A Fuzzy ARTMAP classifier is used to do the classification [14], [15]. Fuzzy ARTMAP is a cognitive neural method combining fuzzy logic and Adaptive Resonance Theory (ART) to create categories of class prototypes to be classified. The classifier has five parameters that determine its characteristics and behavior. They are two learning rate parameters (β), two vigilance parameters (ρ), and a choice parameter (α). For the classifier to achieve good results, an optimization process was run to determine the values for these parameters. To determine the optimum parameters for the classifier, a series of combinations of parameters was considered to calculate the Correct Classification Decisions (CCD). Before the data are used for training and evaluation, they are normalized.

E. Data Analysis

From visual inspection of the measured data, it is clear that radar systems can be distinguished from each other based on the information present in the pulses. The challenge is to translate these differences visible to the eye into mathematical terms.

Characteristics unique to each of the transmitters are visible in the time domain amplitude, frequency and phase data and also in the frequency domain. Visible differences in the pulse widths can be calculated in mathematical terms and associated with the individual radar systems. Similar differences were observed with a number of other features.

An important observation made from the data analysis is the correlation that exists between various features. This indicates that a number of the features convey the same information. Only those features contributing to the separation of radar systems should form part of the feature vector. In Fig 3 this correlation between vectors is shown. Features with high correlation coefficients carry the same information [16].

Linear Discriminant Analysis (LDA) is a useful technique to quantify the separability of features of the input space in almost any classification problem [12]. The main problem with LDA is that it does not provide an effective solution for reducing the dimensions when feature data of different classes are almost totally overlapped. The presence of intrinsic dimensionality neutralizes the intended reduction in dimensionality and the aim to retain only those features that causes peak classification performance. Furthermore, the LDA formulation does not have a direct independent link between the input and output spaces.

The gamma test is an alternative technique to find input features that cause the least uncertainty for a classifier to make accurate class decisions [17], [18]. It was used to evaluate dimensional subset combinations giving the least classification uncertainty. After performing the gamma test on 524,286 dimensional subset combinations out of the original eighteen dimensions, a feature subset was found that matches peak classification performance.

The gamma test has a significant advantage over LDA in that it directly links output class values with input values belonging to those outputs. The gamma test is not sensitive to overlapped features, does not alter (transform) datasets that may cause poor classification performance and can generalize almost any type of classifier. The main disadvantage of the gamma test is that it may take a substantial amount of time to work through all dimensional subset combinations.

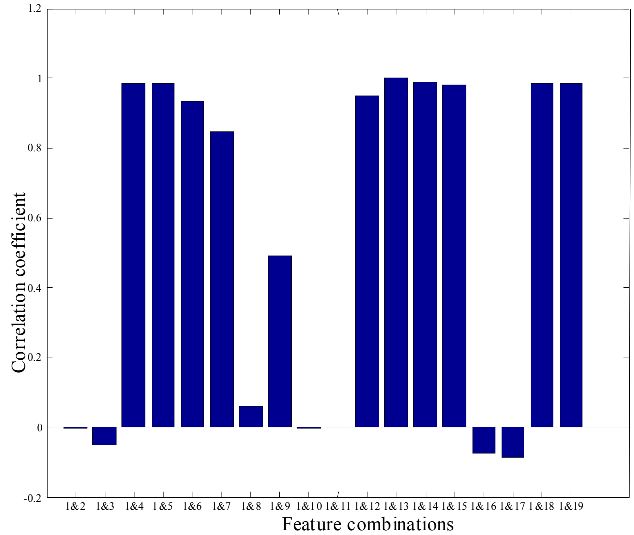

Figure 3. Correlation between one of the features and the rest of the features

From Table I, the classification results using various feature vector sets can be compared. From the results it can be seen which combinations of features give the optimum classification results. This analysis of dimensionality reduction is a practical proof of the curse of dimensionality. Here, classifying with more features does not necessarily provide optimum results. Better classification results are achieved with the optimum set of features.

Obtaining the optimum parameters for the classifier is also an important part of the data analysis. By going through a process of classification with different combinations of classifier parameters, optimum classification results can be obtained. This process is time consuming as the classification process is completed in full for each of the possible combinations of parameters within a given training data set. The combination of parameters which gives the optimum results is then used.

IV. RESULTS

The results obtained can be divided into three different sections, i.e. pulse detection, feature calculation and classification.

The extraction of pulses using the linear phase method is more accurate than using an amplitude threshold method. The linear phase method gives start and stop values that are 25% more accurate than the amplitude method at high SNR. This difference is significant when measuring very narrow pulse widths for example.

From the results of the feature calculation it can be seen that features from the three radars overlap in most of the feature dimensions. Most of the features are clustered together for each of the radar systems which indicate that the individual radar systems occupy a unique part of the feature space. Fig 4 illustrates an example of the amount of overlap of the three radars in two dimensions and Table I summarizes the classification results obtained using different combinations of feature sets.

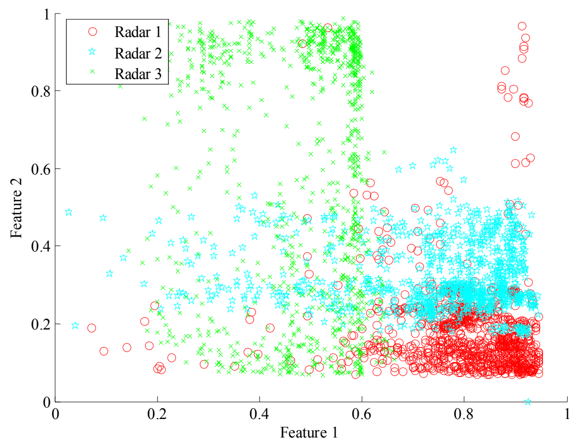

Figure 4. Clustering of two features for three different radars of the same system

TABLE I. CLASSIFICATION RESULTS FOR DIFFERENT COMBINATIONS OF FEATURES

Combination of features	***CCD***
All 18 features	82.32 %
13 features as selected using the correlation method	85.42 %
2 features selected manually	92.15 %
7 features as selected using the gamma test	84.97 %
4 features as selected using LDA	77.74 %
6 features as selected using LDA	74.93 %
8 features as selected using LDA	73.95 %

The classification results are presented according to the dimensionality of the feature vector used as the input to the classifier. The dimensionality of the feature vector is optimized using the dimensionality reduction methods discussed earlier. From the classification results it can be seen that neither the maximum nor the minimum number of dimensions of feature vectors contributes to higher CCD values. The key in obtaining the optimum classification results is to determine the optimum set of features that gives the highest classification results with the least amount of uncertainty.

V. CONCLUSIONS

Using measured radar data, a set of algorithms was developed that can identify a specific radar transmitter from a class of radars of the same kind. Even though the different radars' feature vectors overlapped significantly, good classification results were obtained.

Not all the calculated features are necessarily needed to achieve good classification results. A number of techniques were implemented to determine which combinations of features give good classification performance. The results improved by using the optimum subsets compared to the results when using the full set of features. It is therefore worthwhile to consider dimensionality reduction in the analysis of radar data prior to classification.

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