Evaluation of Waveform Structure Features on Time Domain Target Recognition under Cross Polarization

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Abstract. Classification of aircraft targets from scattered electromagnetic waves is a challenging application, which suffers from aspect angle dependency. In order to eliminate the adverse effects of aspect angle, various strategies were developed including the techniques that rely on extraction of several features and design of suitable classification systems to process them. Recently, a hierarchical method, which uses features that take advantage of waveform structure of the scattered signals, is introduced and shown to have effective results. However, this approach has been applied to the special cases that consider only a single planar component of electric field that cause no-cross polarization at the observation point. In this study, two small scale aircraft models, Boeing-747 and DC-10, are selected as the targets and various polarizations are used to analyse the cross-polarization effects on system performance of the aforementioned method. The results reveal the advantages and the shortcomings of using waveform structures in time-domain target identification.

1. Introduction

The classification of aircraft targets from scattered electromagnetic signals is a challenging problem which is highly altered by aspect dependency [1]. Thus, the scattered signal from a target is highly dependent on the polarization of the incident and reflected fields. An effective target classification strategy should eliminate the adverse effects of the aspect angle while elevating the signal differences due to different target geometries and material type [2]. Recently, waveform structure of time domain scattered signals, which include several hills and valleys, are used for triangular re-modeling of the data. Then, the geometrical information of each triangle is fed to a classifier, where edge lengths and slopes of the triangles as well as the time-interval between triangle peaks constitute a feature set. The effects of noise at low SNR levels are eliminated using a coarse-to-fine approximation strategy that relies on radial basis function networks [3]. Opposed to well-known wavelet multi-resolution analysis using the discrete wavelet transform [4], proposed approach is shown to perform more precise reconstruction of the scattered signal and enable better extraction of the structural features, which eventually result with higher classification rates.

Although the approach described above has been applied to several different target geometries and material types, the experiment conditions are set to some special cases, where only a single planar...
component of electric field is received without cross polarization at the observation point. In this incremental study, the cross-polarization effects are analyzed for the method mentioned above.

The target recognition methods based on polarization diversity generally requires the data of the polarization matrix, which is a $2 \times 2$ complex scattering operator that characterizes a target’s scattering properties. This matrix is obtained from the scattered signals received on both horizontal and vertical polarizations, where Horizontal-Horizontal (HH) and Vertical-Vertical (VV) are both co-polar components and Horizontal-Vertical (HV) and Vertical-Horizontal (VH) are both cross-polar components. There have been many attempts to use the polarization matrix of the target’s scattered signal and other polarization features for target recognition [5]-[7]; however, there has not been the desired success in applying these methods for practical target recognition [1]. Besides these optical region methods, there exist other approaches in literature that are based on neural networks (NN), support vector machines [8], [9] or probabilistic hidden-Markov models and the Bayesian algorithm [10], [11].

Based on the discussions above, in this study, a target identification system for cross-polarization applications is developed. The system initially approximates scattered signals in order to enable robust determination of the peaks and the lobes of the waveform. Then, a triangularization process is carried out to model the scattered signal. Finally, the synthesized model is used to extract several features prior to the target identification. The rest of the paper is organized as follows: Section 2 covers the properties of the targets, the scattered signal data set, methodology (i.e. signal approximation, feature extraction and classification stages) of the developed system. Section 3 presents the application results and draws the conclusions.

2. Scattered Signal Data Set and Methodology

In this study, two small-scale aircraft targets, Boeing 747 and DC-10, are used to test the proposed approximation, feature extraction and classification algorithms. Albeit the number of targets is only two, the polarization invariance property of the suggested target recognition technique can be analyzed since the scattered signal database includes measurements at various polarizations. The aircraft targets to be used in the classifier design are again small-scale models of the actual Boeing 747 and DC-10 aircraft targets with the scale factor of 3/500. The monostatic frequency response measurements of these aircraft targets were done at the ElectroScience Laboratory of the Ohio State University for different polarizations and aspect angles [12]. The list of measurement polarizations and aspect angles for the targets is given Table 1.

| Polarization | HH | VV | X |
|--------------|----|----|---|
| Aircraft Target | Boeing 747 | DC-10 | Boeing 747 | DC-10 | Boeing 747 | DC-10 |
| Aspect Angle (degrees) | 0, 30, 45, 60, 90, 120, 150, 180 | 0, 30, 45, 60, 70, 90, 120, 150, 180 | 0, 30, 45, 60, 90, 120, 150, 180 | 0, 30, 45, 70, 90, 120, 135, 150, 180 |

The operating frequency band of the measurements is 1-12 GHz with 50 MHz frequency resolution (221 points) except the Boeing 747’s HH polarization measurement data. The frequency band of measurements for these exceptional cases is (1.5-12 GHz) with the same frequency resolution. The scattered time signals of both aircraft targets for VV polarization, 90 degree case is given in Figure 1.
Figure 1. The scattered time signals of the small-scale aircraft targets for VV polarization/90 degree case and the frequency band of (1-12 GHz) (blue solid Boeing 747, red dashed DC-10). (a) Full time span, (b) the time interval that contains most of the fluctuations.

The differences between the scattered signals from HH and X polarizations are given for DC10 in Figures 2 and 3, respectively.

Figure 2. The scattered time domain signals for DC-10 at HH polarization and for aspect angles of 120° (blue), 90° (red) and 45° (green)

Figure 3. The scattered time domain signals for DC-10 at V polarization and for aspect angles of 120° (blue), 90° (red) and 45° (green)

Typical scattered signals in Figures 1, 2 and 3 show that these signals consist of fluctuating waveforms and they can be divided into sub-waves. Moreover, these sub-waves can be modeled by a triangularization process, which is based on determination of their amplitudes and durations. In previous studies, it is shown that the differences of these fluctuations can be used to eliminate the aspect angle dependency [3]. In order to do that, structural features, which characterize the waveform of each sub-wave, should be extracted. Specifically, these structural properties correspond to the 'peaks' (both negative and positive), hills and valleys of the scattered signals. Since each peak is assumed to have a lobe around it, these lobes should be found prior to the extraction of the features.

Here, it is important to point that a method utilized to find the peaks and the lobes associated with them should be robust to noise or other high frequency distortions (such as radar glint) such that the recognized peaks represent the main lobes of the signal waveform. Thus, a pre-processing step is needed to remove unwanted high-frequency components while preserving characteristic information of the signal waveform. Unfortunately, the use of smoothing filters is not possible, since they suppress the high frequency components on the entire data. This would also eliminate the highly variable frequency content of the fluctuating waveform and therefore, local analyses are needed. In this respect,
the adaptive approach of MSA can be particularly effective. Hierarchical radial basis function (HRBF) networks offer a coarse-to-fine approach that particularly suits this need [3].

HRBF performs a coarse-to-fine multi-scale analysis by fitting low frequency components first, and then allocates more Gaussian units, where the data contain higher frequencies. The process continues until a pre-defined degree of accuracy is achieved. Since this approach relies on local operations and guarantees a uniform residual error in almost real time, it is used prior to peak detection and feature extraction. Figure 4 illustrates a scattered signal and its approximation created by HRBF, which allow much more robust determination of peaks and their associated lobes.

![Figure 4. Scattered signal with signal to noise ratio equal to (a) 5 dB, (b) 0 dB. It is clear that peak detection gets harder as SNR decreases. (c) HRBF approximated scattered signal.](image)

Instead of estimating the almost arbitrary shape of a lobe, it can be approximated by a simpler geometry while preserving important characteristic information. For this purpose, the coordinates of each lobe is determined such that it can be modeled by a triangle. The corners of the triangles are determined using the following three steps:

1) The maximum or minimum point found by using a peak detection algorithm constitutes the first corner of the triangle (See \(p_1\) and \(p_2\) at Figure 5).
2) The starting point of the lobe found by following the change in the sign of the slope or sign of the data value (i.e. whichever the first) at the left side of the peak constitute the second corner (See \([x_{11}, y_{11}]\) and \([x_{21}, y_{21}]\) at Figure 5)
3) The end point of the lobe found by following the change in the sign of the slope or sign of the data value (i.e. whichever the first) at the right side of the peak constitute the third corner (See \([x_{12}, y_{12}]\) and \([x_{22}, y_{22}]\) at Figure 5)

Next, the following five features are extracted from the triangular model:

1) The distance between the start and the end positions of the lobe constitute the first feature (See the arrows between \([x_{11}, y_{11}]\), \([x_{12}, y_{12}]\) and \([x_{21}, y_{21}], [x_{22}, y_{22}]\) at Figure 5)
2) The distance between the start and the peak positions of the lobe constitute the second feature (i.e. \([x_{11}, y_{11}], p_1\) and \([x_{21}, y_{21}], p_2\) at Figure 5)
3) The distance between the end and the peak positions of the lobe constitute the third feature (i.e. \([x_{12}, y_{12}], p_1\) and \([x_{22}, y_{22}], p_2\) at Figure 5)
4) The slope between the start and the peak positions of the lobe constitute the fourth feature (See \(\alpha_1\) and \(\alpha_2\) at Figure 5)
5) The slope between the end and the peak positions of the lobe constitute the fifth feature (See \(\beta_1\) and \(\beta_2\) at Figure 5)
Finally, inter-peak relations are represented with an additional feature set, which consists of the distances between the peaks. It is clear that the size of this additional feature set depends on the number of peaks found. Moreover, the total number of features also depends on the number of peaks. In this study, the number of peaks is limited, that is only the first fifteen peaks in terms of peak magnitude are considered such that the number of features for each signal become equal.

Figure 5. Two lobes determined around the two peaks ($p_1$ and $p_2$), the triangular models of the lobes and the features determined for each triangular model.

3. Application & Results

Two small scale aircraft models, Boeing 747 and DC-10, are used to test the method developed in this study. Feature vectors extracted for each target for the aspect angles given in Table 1, which generates a data set of 17 samples for HH polarization, 15 samples for VV polarization and 14 samples for X polarization. Since this is a small data set, cross-validation techniques, particularly K-fold analysis, which partitions the data set into K parts, are used [13]. K-fold performs K experiments, in which K-1 folds are used for training and the remaining fold is used for testing. The advantage of K-fold cross validation is that it prevents over-fitting by systematically using all the examples in the data set for both training and testing. The experiments are repeated for different K values including 2, 3 and 4. The best performance is obtained for K=3 and presented in Table 2.

For classification, a Multi-Layer Perceptron (MLP) network is chosen due to its universal approximation property [14]. MLP is trained using back-propagation with adaptive learning rate, which is initialized to 0.01, structured to have one hidden layer with 8 neurons with tangent sigmoid activation functions and an output layer with 2 neurons with linear activation functions. The network goal is chosen to be 0.001 and the maximum number of iterations is determined as 10000 epochs.

The results are shown in Table 2. Correct classification percentage (accuracy), selectivity and specificity metrics are used to measure the system performance. The results show that, although the developed method is successful for HH and VV polarizations, the correct classification percentage using the approximated data significantly decreases for cross polarization (i.e. X). It is observed that the classification performance for X polarization can be increased if more peaks and lobes are used for feature extraction since the scattered signal characteristics are represented in a better way. However, due to the small number of samples in the data set, the classification via supervised learning would not converge for such an extended feature vector.

Table 2. Target recognition results at different polarizations

|       | %     | Accuracy | Selectivity | Sensitivity |
|-------|-------|----------|-------------|-------------|
| HH    | Boeing 747 | 94.25    | 90.82       | 92.13       |
|       | DC-10  | 91.10    | 87.96       | 89.94       |
| VV    | Boeing 747 | 93.55    | 91.24       | 92.82       |
|       | DC-10  | 90.42    | 88.35       | 89.77       |
| X     | Boeing 747 | 86.25    | 84.82       | 85.45       |
|       | DC-10  | 87.64    | 82.96       | 87.86       |
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