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AUTOMATIC TARGET CLASSIFICATION IN GMTI AIRBORNE SCENARIO

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ABSTRACT

Ground moving radar target classification is one of the recent research issues that has arisen in an airborne ground moving target indicator (GMTI) scenario. This work presents a novel technique for classifying individual targets depending on their radar cross section (RCS) values. The RCS feature is evaluated using the Chebyshev polynomial. The radar captured target usually provides an imbalanced solution for classes that have lower numbers of pixels and that have similar characteristics. In this classification technique, the Chebyshev polynomial's features have overcome the problem of confusion between target classes with similar characteristics. The Chebyshev polynomial highlights the RCS feature and is able to suppress the jammer signal. Classification has been performed by using the probability neural network (PNN) model. Finally, the classifier with the Chebyshev polynomial feature has been tested with an unknown RCS value. The proposed classification method can be used for classifying targets in a GMTI system under the warfield condition.

Keywords: Airborne radar; Chebyshev polynomial; PNN; RCS; Target classification

1. INTRODUCTION

In automatic target recognition (ATR), one of the significant aims is to separate the different target types (Kubrusly & Levan, 2009; Nejad & Zakeri, 2011). Van Dorp and Groen (2008) used radar echo signals as characteristic features for target recognition. Over the past few years, technologies for target identification, border security, and controlled access to critical infrastructures have become very important issues. In this paper, we focus our attention on the classification of radar targets after clutter and jammer suppression in an airborne radar scenario. A simulated environment has been developed for capturing radar data. The simulation of the flying radar is done with the consideration of a ground clutter. The clutter is generated near the target zone, and the existence of a wideband Gaussian-distributed barrage-jammer is introduced. For clutter and jammer suppression, the sample matrix inversion (SMI) method has been used; this includes the clutter and jammer covariance matrix with the subspace-based Digital BeamForming (DBF) algorithm (Guerci, 2013). The DBF algorithm is employed to cover a detection area of a long range (2000 m) and an angular orientation of [90^o, 35.26^o] with respect to the RADAR platform flying in an airplane under the airborne scenario. The airplane actually carries spaceborne radar with its baseband source using a linear frequency-modulated (LFM) waveform. The radio frequency (RF) carrier is used as a single 3 GHz oscillator. The proposed target classification can be used in airborne radar for a ground moving target indicator

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(GMTI) system under the warfield condition. In this paper, an ancient approach for the automatic classification of radar emitter signals is proposed. The targets are classified on the basis of returned energy to the radar cross section (RCS) values, which are taken at different aspect angles. The feature extraction stage is the most important (Zhang & Zhou, 2011; Zhang & Lei, 2011) in classification. In general, the Fourier transform has been used for some expert radar target recognition applications. Some authors (Golub et al., 1999) show the use of discrete wavelet transform in expert radar target recognition and suggest that this technique is very useful because the original feature space can be augmented by discrete wavelet transform coefficients. The proposed approach measures the features by using the Chebyshev polynomials. The coefficients of the Chebyshev polynomials are obtained by recurrence relation. Here, in this method, we have used first-order polynomials. The order of the polynomials controls the curvature of the surface, and in this paper, the polynomial interpolation technique is used to obtain general geographic patterns of change in a variable. Thus, we cannot use a higher-order polynomial for the feature value; otherwise, the general pattern of the target will be hidden. The proposed approach can easily be applied to any number of emitters and any number of measured features without the exponential growing of the required computations. The final results show the feasibility and effectiveness of the proposed classification approach.

Chebyshev polynomials are computationally more efficient than other trigonometric functions, with very powerful non-linear approximation capacity for classification in the higher dimensional plane (Parikh et al., 2010). The Chebyshev polynomial has been used to find out the polynomial that passes through the points of the given radar captured data. Here, the dataset has a high degree of precision, so to approximate the function, we have chosen the collocation method to find the Chebyshev polynomial approximation. For accurate polynomial approximation, it is most important to find the exact boundary value for the function. The Chebyshev polynomial approximation is for the function $f(x)$ over the interval [-1,1]. One of the distinguished properties of the Chebyshev polynomial is that it preserves the properties of the nodes because the error for approximation is a lot less. Chebyshev polynomial expansion efficiently approximates the application of a spectral graph wavelet transform, which is a specific example of a union of graph Fourier multipliers. In this paper, we have used the Chebyshev polynomial approximation method for evaluating the features of targets and show how this property can be used for radar target classification. After the feature extraction phase, a classification procedure follows. An artificial neural network (ANN) algorithm is employed to serve as a classifier. ANNs have recently been applied for various categories of data analysis. Commonly used network models and some extended forms include the multi-layer perceptron (MLP), Bayesian neural network (BNN) (King & Sinha, 2001), time adaptive self-organizing map (TASOM) (Shah-Hosseini & Safabakhsh, 2003), self-organizing tree algorithm (SOTA) (Mateos et al., 2002), etc. The probabilistic neural network that Specht (1998) introduced is often an excellent pattern classifier in practice. The network model is commonly regarded as one variant of radial basis networks due to the adopted radial transfer functions in the hidden layer, and it is essentially based on the well-known Bayesian classification technique. We have trained the probabilistic neural network (PNN) classifier with the Chebyshev polynomial feature set, and we form a practical automatic radar target classification scheme after the suppression of clutter and jammer in the airborne scenario. Figure 1 represents the block diagram for target detection in a GMTI scenario.

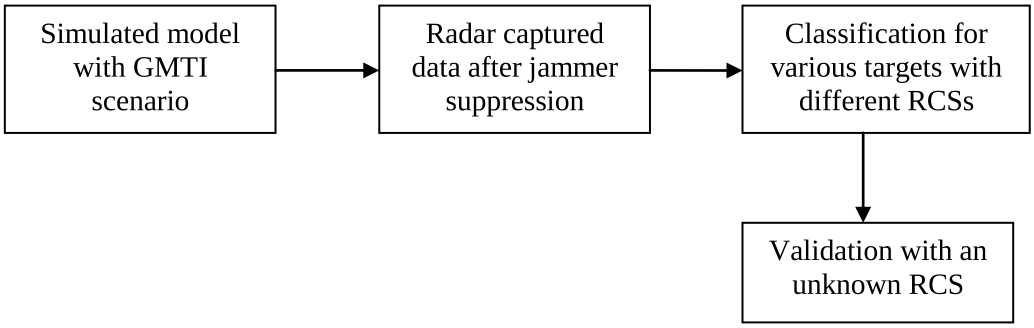

Figure 1 Block diagram for target detection in GMTI scenario

2. RADAR SYSTEM DESIGN

DBF technology (Guerci, 2013) has been designed for jammer and clutter suppression with uniform rectangular phased-array antennas in the MATLAB simulation model. The DBF algorithm is employed to cover a detection area of a long range (2000 m) and an angular orientation of [90^{o}, -35.26^{o}] with respect to the RADAR platform flying in an airplane under the airborne scenario. Utilizing the MATLAB object “phased.IsotropicAntennaElement,” the antenna elements are designed. Each antenna element has its operating frequency range [0.3 GHz to 5 GHz]. However, the proposed spaceborne radar operates at RF = 3 GHz. The radar platform is located at a height of 1000 m above the battleground. Another object, “phased.LinearFMWaveform,” is used to design the baseband source of the airborne radar. The MATLAB object “phased.URA” (object constructs a uniform rectangular array) is used to construct the uniform rectangular array of a [10×10] dimension having an element spacing of 0:05 m. The “phased.Radiator” object implements a narrowband signal radiator that up-converts the baseband signal to the RF of 3 GHz. Similarly, the “phased.Collector” object implements a narrowband signal collector, which collects the RF stimuli from each of the 100 elements of the URA and finally down-converts them to the baseband waveform. The input signals to the radar collector are multiple plane waves impinging on the entire array this way all collecting elements receive each plane wave. The target is designed to operate at 3 GHz, and its type is non-fluctuating, having a mean RCS of 1 m^2. The target platform is located at the coordinate of [1000, 1000, 0] in the ground plane. The target moves with a velocity of 30 m per sec. The presence of the Gaussian distributed jammer is considered in this scenario, and the location of the jammer is taken in the first case at [Azimuth=90^0, Elevation=0^0], in the second case at [Azimuth = 120^{o}, Elevation = 0^{o}], and similarly, in the third case at [Azimuth = 60^{o}, Elevation = 0^{o}]. The sample matrix inversion method under a heavy jammer and clutter scenario gives rise to a signal-to-clutter and jammer ratio (SCJR) of 21.7 dB. Figure 2 shows the clutter and jammer condition in a GMTI scenario (Bhaskar et al., 2015).

3. FEATURE EXTRACTION BY CHEBYSHEV POLYNOMIAL

The range of values for radar raw data varies widely due to pulse repetition frequency and the wavelength of the radar, so it is always necessary to scale the data for further computation. In this paper, the raw data are first scaled, as feature extraction for the scaled data reduces the computational time and minimizes the error rate for polynomial approximation. Scaling has been done by dividing the whole dataset with the mean value. Figures 2, 4, 5, and 6 are figures for the scaled data. The scaled-data feature has been evaluated by using the Chebyshev polynomial technique.

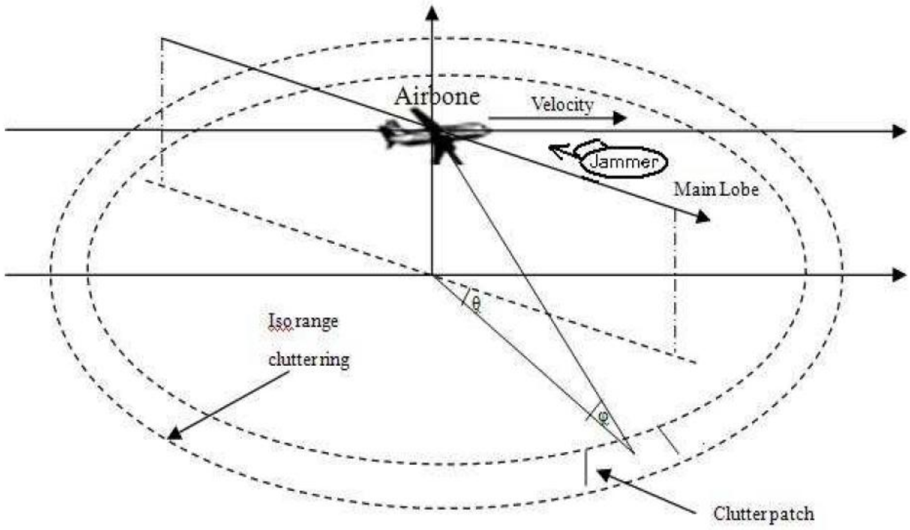

Figure 2 Clutter and jammer condition in airborne scenario (Bhaskar et al., 2015)

The Chebyshev polynomial has been generated by using the recurrence relation:

$$t_0(x) = 1 \tag{1}$$

$$t_1(x) = \frac{2x + 1 - N}{N} \tag{2}$$

$$t_p(x) = \frac{(2p-1)t_1(x)t_{p-1}(x) - (p-1) - \frac{(p-1)^2}{N^2} t_{p-2}(x)}{p} \tag{3}$$

Since the Chebyshev polynomials are exactly orthogonal in the discrete coordinate space of the image, for an $N \times N$ image, we first seek discrete orthogonal polynomials $t_n(x)$ that satisfy the condition:

$$\sum_{x=0}^{N-1} t_m(x)t_n(x) = \rho(n, N)\delta_{mn} \tag{4}$$

where $m, n = 0,1,2,....N-1$ and $\rho(n.m)$ is the squared norm of the polynomial set t_n. The classical discrete Chebyshev polynomial (3) satisfies the property of orthogonality (1) with

$$\rho(n, m) = \frac{N(N^2-1)(N^2-2^2)...(N^2-n^2)}{2n+1} \tag{5}$$

where $n = 0, 1, 2,..N-1$ and have the following recurrences:

$$(n+1)t_{n+1}(x) - (2n+1)(2x - N + 1)t_n(x) + n(N^2 - n^2)t_{n-1}(x) = 0 \tag{6}$$

However, the Chebyshev polynomials as defined above, together with their norms, become numerically unstable for large values of N. Also, it can be easily verified that the magnitude of t_n grows at the rate of N^n.

We therefore further scale the Chebyshev polynomials $t_n(x)$ by a factor N^n, and in this way, it is suitable for image analysis. Then, the Chebyshev polynomial can be defined as:

$$T_{pq} = \frac{1}{\rho(p, N)\rho(q, n)} \sum_{x=0}^{N-1} \sum_{y=0}^{N-1} t_p(x) t_q(y) f(x, y) \tag{7}$$

where $p, q=0,1,2.....N\text{-}1$ and

$$\rho(p, N) = \frac{N(1 - \frac{1^2}{N^2})(1 - \frac{2^2}{N^2})..........(1 - \frac{p^2}{N^2})}{2p + 1} \tag{8}$$

The image intensity function $f(x, y)$ has a polynomial representation given by:

$$f(x, y) = \sum_{p=0}^{N-1} \sum_{q=0}^{N-1} T_{pq} t_p(x) t_q(y) \tag{9}$$

The coefficients T_{pq} are the Chebyshev coefficients defined in Equation 4. The above result follows when the left-hand side of Equation 1 is applied as an operator to both sides of Equation 4. Here, the feature has been evaluated by the Chebyshev polynomial for several reasons: (i) Chebyshev polynomials are sequences of orthogonal functions defined for x $\in [0,1]$, and (ii) the above recurrence relation for Chebyshev polynomials is readily amenable to efficient computation.

The radar signal is nothing but the measurement of the Doppler of a signal. Due to the scattering of the atmospheric elements, the returned signal from atmospheric layers is very weak in terms of power. The received backscattered signals, called radar returns, are associated with a lot of noise. In this paper, we demonstrate how the Chebyshev polynomial co-efficient has been used as a feature extraction method. The optimality of the Chebyshev polynomial is that it preserves all theoretical properties, as it does not involve any kind of approximation. The optimality criterion of the Chebyshev polynomial with the Fourier transform is that it exhibits the narrowest main-lobe width for a selected/given side-lobe level. Also, the Chebyshev polynomial coefficient exhibits equal ripple for the specified side-lobe level. In the presence of the Gaussian distributed jammer, false targets are generated, and it is difficult to suppress or identify by radar, especially when the main-beam false target occurs. In this case, the distributional characteristics of the true and false targets are similar. Based on the recurrence relation, the Chebyshev polynomial is used. The novelty is its simple non-parametric technique for the identification of the true target. Chebyshev polynomials are used to construct new kernels and show their computational efficiency with the probabilistic neural net (PNN) classifier.

4. PNN CLASSIFIER

The PNN classifier uses the following estimator for the probability density function:

$$f_A(x) = \frac{1}{(m_A)(\sigma^n)(2\pi)^{\frac{n}{2}}} \sum_{i=1}^{m_A} \exp[-\frac{(x - x_{Ai})^T (x - x_{Ai})}{2\sigma^2}] \tag{10}$$

Equation 10 (Fausett, 2006) represents the estimation of the probability density functions of $f_A(x)$ and $f_B(x)$ from the training patterns. In Equation 10, x_{Ai} is the ith pattern from class A, n is the dimension of the input vectors, m_A is the number of training patterns in class A, and σ is the smoothing parameters, which is equal to the standard deviation of the Gaussian distribution.

The PNN classifiers use a strategy, is similar with Bayes' probability strategy for error minimization, which allows for a strict mathematical proof of their working mechanics. When solving problems related to classification, the classic neural network estimates the density of probabilities for every class and by comparing them chooses the most probable class, i.e., the classifier applies each observation to one of several classes.

5. EXPERIMENTAL RESULTS

In the captured data, three classes of targets exist depending on their RCS values. The RCS values are: 1 m^2 is considered class 1, 2.2 m^2 is considered class 2, and 3.6 m^2 is considered class 3. Figures 3, 5, and 7 contain the data plot for the class 1, class 2, and class 3 targets after clutter and jammer suppression.

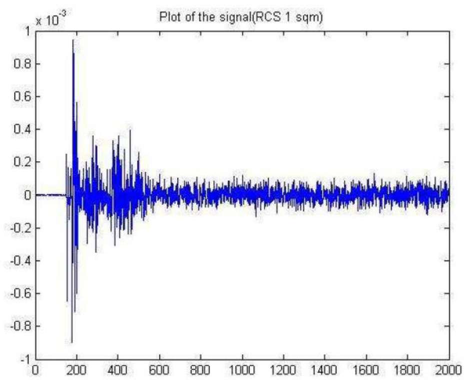

Figure 3 Plot for the original signal (RCS-1m^2)

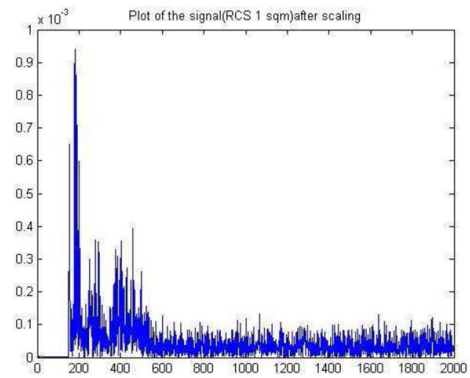

Figure 4 Plot for the scaled signal (RCS-1m^2)

Figures 4, 6, and 8 include the plot of scaled data for the target classes 1, 2, and 3, respectively.

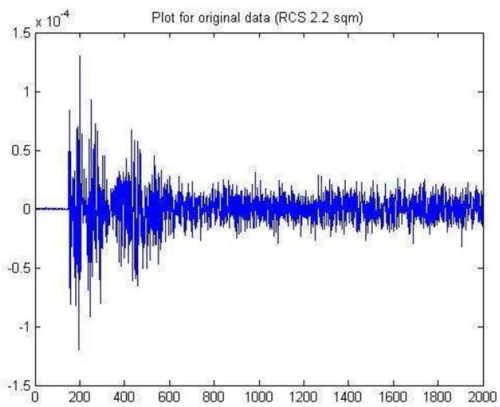

Figure 5 Plot for the original signal (RCS-2.2m^2)

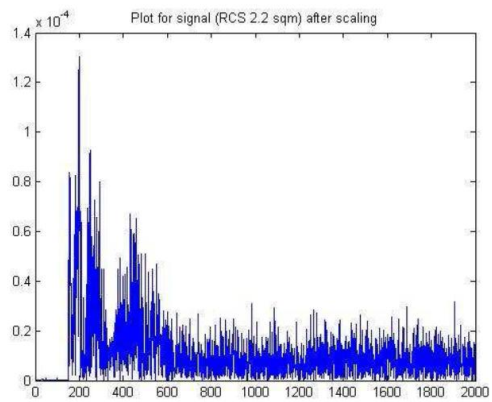

Figure 6 Plot for the scaled signal (RCS-2.2m^2)

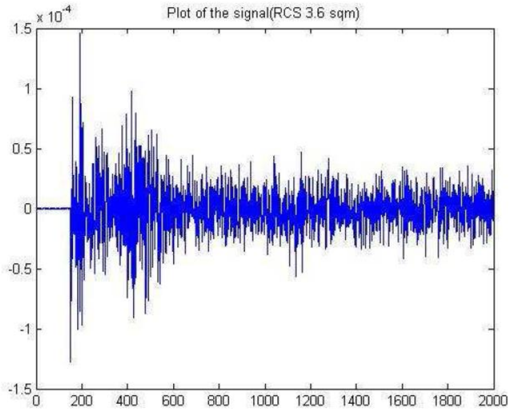

Figure 7 Plot for the original signal (RCS-3.6m^2)

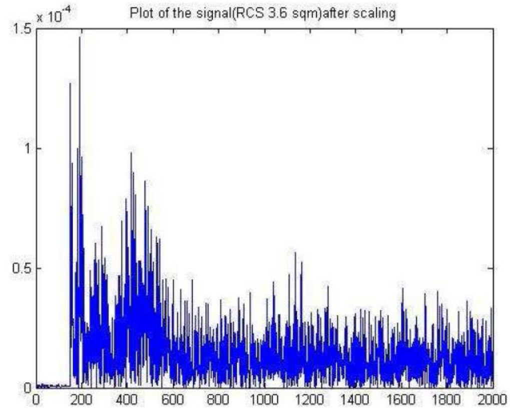

Figure 8 Plot for the scaled signal (RCS-3.6m^2)

The main goal of this paper is to create a new target classification approach based on supervised classification, in which the characteristics of clusters are introduced to the classifier depending on their RCS values for classification. In our supervised classifier, sample pixels from the targets for three different classes are extracted, and then, Chebyshev polynomial coefficients of these pixels are used for training the method.

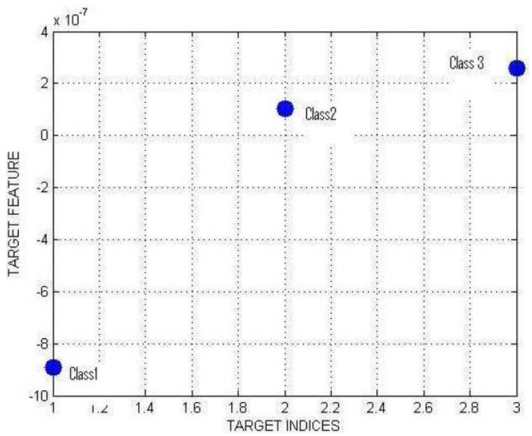

Figure 9 Plot for three feature vectors evaluated by using Chebyshev polynomial

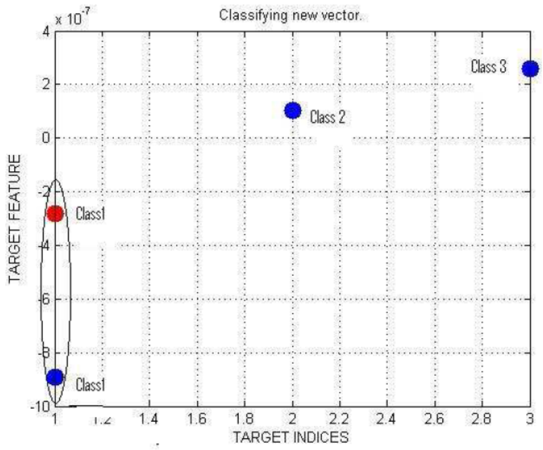

Figure 10 Classification of unknown target via PNN classification approach

In the training phase, the RCS data of the training target are collected in the compact range. Figure 9 includes the feature plot for three classes determined after evaluating Chebyshev polynomial coefficients through recurrence relation. Figure 10 includes the classification result obtained after using PNN classifier. The unknown target have the RCS of 1.6 m^2. In this figure, the unknown classified target is shown by the red-colored dot. By visualizing this, it is easy to determine that the unknown target falls under the category of RCS 1 m^2, which is labeled as class 1.

6. COMPARISON WITH OTHER METHOD

A comparison analysis with two different feature evaluation methods has been done on the same data. Ahmad and Sha'ameri (2015) proposed the ARTAC system by analyzing energy and frequency for various signals. They used the Monte Carlo simulation model. Du et al. (2016) proposed a micro-Doppler feature for discriminating between the targets. Table 1 shows the classification accuracy with ARTAC, micro Doppler, and the Chebyshev polynomial feature extraction methodology, and a significant improvement was found with the Chebyshev polynomial feature. This shows the effectiveness of the proposed feature evaluation technique.

Table 1 Comparison analysis with two different feature evaluation techniques

Feature extraction method	Signal-to-Noise ratio	Classification accuracy
ARTAC, energy, Frequency	≥13 dB	98.23%
Micro Doppler	≥13 dB	98%
Chebyshev Polynomial	≥13 dB	100%

7. CONCLUSION

In this paper, we have proposed a feature extraction method by using the Chebyshev polynomial technique for an airborne radar target. This method can be used for the automatic classification of an airborne radar target in a GMTI scenario when intra-class variances between the targets are significantly small. The translation trajectory is approximated by the Chebyshev polynomial as a feature and improves the approximation accuracy. The proposed methodology can be applied in a warfield GMTI scenario for the classification of targets depending on their RCS values. The method automates the entire radar target classification system in a GMTI scenario. The RCS feature represented by the Chebyshev polynomial coefficient provides a robust classification system for radar targets.

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