Spherical Target Recognition using Time-Domain Multiscale Approximation of Scattered Signals

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Abstract. Classification of similar shaped objects from scattered electromagnetic waves is a difficult problem to solve, as it heavily depends on the aspect angle. Eliminating the effects of the aspect angle is possible by extracting distinguishable features from the scattered signals. These features should be robust to noise effects especially at SNR levels, where noise effects become dominant on the scattered signal. In this paper, we propose a target classification method, which uses a structural feature set extracted from scattered signal. Prior to feature extraction, a multi-scale approximation is performed using hierarchical radial basis function network topology to suppress the effects of noise on scattered signal. After principle component analysis, k-fold cross validation based experiments is performed. Results show that spherical targets are recognized successfully up to -10dB SNR.

1. Introduction

The classification of similar targets from scattered electromagnetic signals is a challenging problem due to the strong dependency to aspect angle [1]. In order to classify a target effectively, distinguishable features should be extracted and adequately processed to gain independency from the adverse effects of aspect angle [2]. Moreover, these features should be robust to noise, which can alter scattered signal characteristics significantly.

Recently, structural properties of time domain scattered signals are used effectively in target recognition [3]. As these properties are based on hill-valley detection, corresponding features are very sensitive to noise. In this study, noisy scattered signals are approximated via a set of hierarchical radial basis functions. Opposed to well-known wavelet multi-resolution analysis using the discrete wavelet transform [4], proposed approach reconstructs the signal from low frequency components to high and this allows better extraction of features from noisy scattered signals.

At each layer of the hierarchy, a number of Gaussian units are used to approximate to the valleys/hills in the scattered data. The structural parameters of these units (i.e. centers, widths and amplitudes) are predefined for each layer and the number of these units is determined using a performance criterion. Finally, a combination of the selected units is used to create an approximation. For evaluation of the proposed technique in target classification, cross validation learning strategy [5] is used. The results show that, up to -10 dB SNR, proposed method can effectively be used for target classification.
2. Method

2.1. Generation of Data

The scattered electric fields can be expressed in terms of Hertz and Debye potentials as in [2]. In this study, the scattered signals are calculated by the analytical solutions using these potentials. These analytical expressions are extracted for a plane wave excitation which is linearly polarized in x-direction and propagates in z-direction (Figure 1).

The far field scattered responses are computed using MATLAB 7.1 in frequency domain over a bandwidth from zero to 12 GHz at 873 frequency sample points with frequency resolution of 13.75 MHz which can be regarded as resonance region. These responses are also obtained at $\phi = \pi/2$ plane, with a radial distance of 72 cm from the sphere center, for twelve different Bistatic Aspect Angles (BAA), $180 - \theta = \theta_b = 10^\circ, 20^\circ, \ldots, 180^\circ$ degrees as shown in Figure 1.

After getting the scattered signals in frequency domain, inverse fast Fourier transformation was applied to get time-domain scattered fields. This allows scattered signals up to 5 ps resolution, which can be used to observe the frequency range below 12 GHz.

The resulting time signals, which are used throughout the simulation, have 1024 sample points with a total time span of 5.115 ns (Figures 2 and 3). The noisy scattered time domain signals at all the aspect angles stated above are obtained at the signal-to noise ratio (SNR) levels of 10, 0 and -10 dB to be used for classifier design and for performance testing.

Figure 1. The geometry of the problem used to generate electromagnetic signals scattered from the spherical target.

Figure 2. The scattered time domain signals for the dielectric sphere of radius 2.4 cm at BAA of $60^\circ$ (blue), $90^\circ$ (red) and $120^\circ$ (green).

Figure 3. The scattered time signals for the dielectric sphere of radius 1.8 cm (blue), 2.4 cm (red) and 3.0 cm (green) at BAA of 100°.
2.2. Structural Feature Extraction Strategy

Typical scattered signals in Figure 2 and Figure 3 show that these signals can be divided into four sub-waves. Analysis of these sub-waves shows that the amplitude and duration of these four sub-waves differ depending on the radius of the target. Thus, if aspect angle effects can be eliminated, these sub-wave properties (i.e. structural features) can be used to classify similar spheres with different radii.

Considering the fluctuating waveform, which is the common aspect for all signals we dealt with, extraction is built upon analyzing the 'peaks' (both negative and positive) in the signal. For each peak in the signal, 5 features are extracted. In addition, distances between the maxima/minima points of adjacent peaks are calculated. Hence, 6n-1 feature is obtained for a single scattered wave, where n is the number of detected peaks in the signal. The features are illustrated in Figure 5.

2.3. Hierarchical Use of Gaussian Units For Multi-scale Approximation of Scattered Signal

Extracting a feature set from noisy data is based on estimating local extremum points and zero-crossings by means of certain rules. Thus, the representation capability of the features relies on finding these important points on the signal. Since, it has been experimentally shown that the features extracted from a low-SNR signal provide better recognition performance [3], the noise effects over the signal should be suppressed prior to feature extraction.

The approximation function, \( f(x) \), to the scattered signal using bell shaped Gaussian functions can be defined as;

\[
f(x) = \sum_{j=1}^{N} w_j \cdot g(x - c_j; \sigma_j)
\]
where \( c_j \in \mathbb{R} \) corresponds to the center of the \( j \)th Gaussian unit, \( \sigma_j \in \mathbb{R} \) to the width and \( w_j \in \mathbb{R} \) corresponds to the amplitude of the \( j \)th Gaussian unit. In its most general form, the \( j \)th Gaussian unit in the \( i \)th layer is defined by \( g_{ij}(\cdot) = \exp \left( -\left( \frac{1}{\sigma_{ij}} \right)^2 \right) \).

The proposed approximation technique performs an approximation of \( f(x) \) using the sum of \( K \) approximations \( \{l_i(\cdot)\}_{i=1,2,\ldots,K} \);

\[
f(x) = \sum_{i=1}^{K} l_i(x)
\]

Herein, approximation layers, \( l_i(\cdot) \)'s, are the sets of Gaussian functions, which have predefined centers, widths and amplitudes for that layer. In order to accomplish a multi-scale task, the Gaussian units become denser in position, narrower in width and smaller in amplitude as the levels proceed. Thus, each layer, \( l_i(\cdot) \), consists of a linear combination of Gaussian units, which are selected through a performance criteria to be used for that layer.

Consider that \( l_i(\cdot) \) is composed of \( M_i \) Gaussian units. Then, an approximation layer can be defined as,

\[
l_i(x) = \sum_{j=1}^{M_i} w_{ij} \cdot g(x - c_{ij}; \sigma_{ij})
\]

As a result, the approximation uses \( M = \sum_{j=1}^{M_i} M_i \) Gaussian units to approximate the scattered signal.

After approximating the function by using the Gaussian units found for a layer (Figure 4b), a residual is calculated point-wise, i.e. for each point \( x^n \) of the original scattered signal;

\[
r_1(x^n) = f(x^n) - l_1(x^n)
\]

The next approximation layer considers the residual signal found in the previous layer as the new function to be approximated. The new Gaussian units having predefined center, width and amplitude for that layer is inserted. The performance criterion is used again to select which ones to use the corresponding residual signal. The general expression of a residual scattered signal to be approximated as \( i \)th layer is given as;

\[
r_{i-1}(x^n) = f(x^n) + \sum_{j=1}^{i-1} w_{ij} \cdot g(x - c_{ij}; \sigma_{ij}) - l_{i-2}(x^n)
\]

To approximate the scattered signal, this procedure continues for several layers until the approximation error approaches a predefined value. The algorithm to accomplish this task and its pseudo code is given below;

1. Signal is divided into frames, which have equal lengths.
2. For each frame, Gaussian curves are added into a new array, which has the same length with the frame defined in 1. Gaussian curves are placed in the middle of the frame symmetrically and designed to have a standard deviation, which is equal to 0.125 of the frame length. Amplitude is chosen to be equal to 1/100 of maximum value of the signal.
3. Inside the frame, Gaussian curves are added until the error between approximation and original signal is smaller than a predefined error criteria.
3. Application & Results

Four spherical targets, which have radius of 1.8cm, 2.4cm, 3.0cm, and 3.6cm, respectively, are used to test the method developed in this study. Feature vectors extracted for each sphere for 18 BAA, which generates a data set of 72 samples. The same procedure is also applied for scattered signal, which have added noise at SNR= 10, 0 and -10 dB levels.

Since this is a small data set, cross-validation techniques [5] are used to measure the performance of the technique. Among several possibilities, K-fold partitioning is chosen [5]. K-fold technique partitions the data set into K parts and 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. K=9 is chosen as it is experienced to provide higher performance.

For classification, a Multi-Layer Perceptron (MLP) network [6], which is trained using back-propagation with adaptive learning rate, is employed. The MLP has one hidden layer with 6 neurons with tangent sigmoid activation functions and an output layer with 4 neurons with linear activation functions. The network goal is chosen to be 0.001 and the maximum number of iterations is determined as 15000 epochs. The adaptive learning rate is initialized to 0.01.

The results are shown in Tables 1-6. Tables 1 and 2 compares correct classification percentage (accuracy) for classification of the noisy data and the approximated data, respectively. The results show that, although the performances of both strategies are close to each other for high SNR levels, the correct classification percentage using the approximated data outperforms the use of original scattered signal as SNR level decreases. For instance, at -10dB SNR level, the classification performed using the features extracted from approximated scattered signal performs 4.40% and 6.43% higher accuracy for spheres 1 and 2, while the accuracy for 3 and 4 remains the same. Similar results are also achieved for Selectivity (Tables 3-4) and Specificity (Tables 5-6) metrics.

| Table 1. Target recognition results (Accuracy) using features extracted from raw scattered data |
|---------------------------------------------|
| **Accuracy %** | **Sphere-1** | **Sphere-2** | **Sphere-3** | **Sphere-4** |
|-----------------|--------------|--------------|--------------|--------------|
| **SNR=∞**       | 95.83        | 92.55        | 87.53        | 88.57        |
| **SNR=10 dB**   | 94.03        | 86.94        | 82.13        | 89.31        |
| **SNR=0 dB**    | 88.19        | 74.81        | 68.66        | 76.39        |
| **SNR=-10 dB**  | 75.60        | 61.53        | 69.95        | 73.75        |
Table 2. Target recognition results (Accuracy) using features extracted from approximated data

| SNR          | Sphere-1 | Sphere-2 | Sphere-3 | Sphere-4 |
|--------------|----------|----------|----------|----------|
| SNR=∞        | 96.25    | 94.82    | 92.13    | 93.10    |
| SNR=10 dB    | 95.79    | 94.82    | 91.11    | 92.64    |
| SNR=0 dB     | 93.61    | 90.28    | 84.26    | 88.24    |
| SNR=−10 dB   | 80.00    | 67.96    | 69.76    | 73.70    |

Table 3. Target recognition results (Sensitivity) using features extracted from raw scattered data

| SNR          | Sphere-1 | Sphere-2 | Sphere-3 | Sphere-4 |
|--------------|----------|----------|----------|----------|
| SNR=∞        | 94.25    | 82.22    | 77.40    | 73.88    |
| SNR=10 dB    | 90.74    | 72.03    | 69.63    | 72.40    |
| SNR=0 dB     | 77.03    | 47.40    | 42.22    | 49.44    |
| SNR=−10 dB   | 50.74    | 30.92    | 41.29    | 38.70    |

Table 4. Target recognition results (Sensitivity) using features extracted from approximated data

| SNR          | Sphere-1 | Sphere-2 | Sphere-3 | Sphere-4 |
|--------------|----------|----------|----------|----------|
| SNR=∞        | 94.63    | 89.07    | 87.03    | 81.85    |
| SNR=10 dB    | 94.07    | 93.14    | 80.74    | 80.74    |
| SNR=0 dB     | 87.96    | 84.81    | 69.63    | 70.36    |
| SNR=−10 dB   | 65.18    | 42.59    | 30.74    | 38.33    |

Table 5. Target recognition results (Specificity) using features extracted from raw scattered data

| SNR          | Sphere-1 | Sphere-2 | Sphere-3 | Sphere-4 |
|--------------|----------|----------|----------|----------|
| SNR=∞        | 96.35    | 95.98    | 90.86    | 93.08    |
| SNR=10 dB    | 95.12    | 91.91    | 86.29    | 94.39    |
| SNR=0 dB     | 91.91    | 83.95    | 77.46    | 85.37    |
| SNR=−10 dB   | 83.88    | 71.72    | 79.50    | 85.43    |

Table 6. Target recognition results (Specificity) using features extracted from approximated data

| SNR          | Sphere-1 | Sphere-2 | Sphere-3 | Sphere-4 |
|--------------|----------|----------|----------|----------|
| SNR=∞        | 96.79    | 96.72    | 93.82    | 96.85    |
| SNR=10 dB    | 96.35    | 95.37    | 94.56    | 96.60    |
| SNR=0 dB     | 95.46    | 92.06    | 89.13    | 94.19    |
| SNR=−10 dB   | 84.93    | 76.41    | 78.76    | 85.49    |

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