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Receiving Angle Extraction for Bistatic Radar Target Recognition

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Abstract. When the target of interest is determined, the transmitter and receiver positions of bistatic radar are of great importance at the aspect of radar target classification. The radar cross section (RCS) of a target varies with these positions, and the target classification performance is considerably influenced by RCS. In this study, the target classification performance using the bistatic RCS of four different wire targets was analyzed. Time-frequency analysis and effective compression techniques are used for target feature extraction from the bistatic scattering data of each target, and a multilayered perceptron (MLP) neural network is used as a classifier. The optimum receiver position is found by comparing the calculated classification probabilities while changing the position of the bistatic radar receiver. The simulation results show that an optimally positioned bistatic radar yields better classification results, demonstrating the importance of the positions of the transmitter and receiver for bistatic radar.

Keywords: Bistatic radar, Radar target classification, Optimum bistatic angle, Target feature extraction

1 Introduction

RCS contains useful information for radar target classification, such as scattering centers and natural resonance frequencies. The scattering centers on the target are related to the early-time response and natural resonance frequencies of the target are related to the late-time response. The early-time response occurs while the field passes across the target, whereas the late-time response occurs after the field completely passes across the target [1]. The scattering centers and natural resonance frequencies are used as feature vectors for radar target classification. We use time-frequency transforms to extract these feature vectors simultaneously.

In this work, we use the calculated bistatic scattering data of four different wire targets while changing the receiver position, and extract feature vectors using the short time Fourier transform (STFT) and continuous wavelet transform (CWT) with

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effective compression techniques. Then, a multilayered perceptron (MLP) neural network is used as a classifier. Using this process, the receiver position having the best performance may be found by comparing the calculated classification probabilities.

2 Proposed Method

In this paper, we propose the optimum bistatic angle extraction for radar target classification using this process. We assume that the targets of interest and radar operating frequency are determined previously. The proposed algorithm is as follows:

Step 1) Bistatic scattering data in the frequency domain are calculated using an electromagnetic simulation tool or measured using a bistatic measurement system. We assume that the transmitter Tx is located at 0° and the receiver positions are changed from Rx 1 to Rx *Kn* with a uniform interval, where *Kn* is the total number of receiver positions. At each bistatic angle, the targets are also rotated from 0° to a specific aspect angle limit.

Step 2) The transient response of the target is then obtained by performing an inverse Fourier transform (IFT) of the stepped-frequency bistatic scattering data.

Step 3) We extract feature vectors from the transient response using the compressed STFT and CWT matrices. The detailed feature extraction methods are explained in the following sections.

Step 4) The feature vectors are divided into training sets and test sets. The training feature vectors are used for training the MLP neural network classifier. The trained neural network provides the classification result for the test feature sets.

Step 5) At each bistatic angle, we repeat from step 2 to step 4 and obtain the target classification results. We compare the classification results of all bistatic angles, and the bistatic angle which has the best classification result is determined as the optimum bistatic angle for target classification.

3 Simulation Results

To analyze the radar target classification performance of the bistatic scattering data, we first used simulation data of four different wire targets. Figure 1 shows the stick-aircraft target geometries used in the simulations. Targets A and B, as well as C and D, have the same length, but different wing angles. To obtain the scattering field we used the method of moments (MoM) option in FEKO. FEKO is a commercial EM simulation tool, and is based on a 3D grid. The frequency range was chosen as 7.8125 MHz to 1 GHz, with 128-point samplings and with HH polarization. The nose of wire targets is placed at the position (0,0,0), and the wire targets are placed in the x-y plane. The bistatic scattering field was calculated for each aspect angle of a counterclockwise rotated target from 0° to 150° using a 1° aspect angle step, where the transmitter was located at 0° and the receiver was located at a specific bistatic angle. Using the above process, the bistatic scattering field of 0° ~ 150° aspect angles was calculated for the receiver positions 15°, 30°, 45°, 60°, 75°, 90°, 105°, 120°, 135°, 150°, 165° to compare the target classification performance for each receiver position.

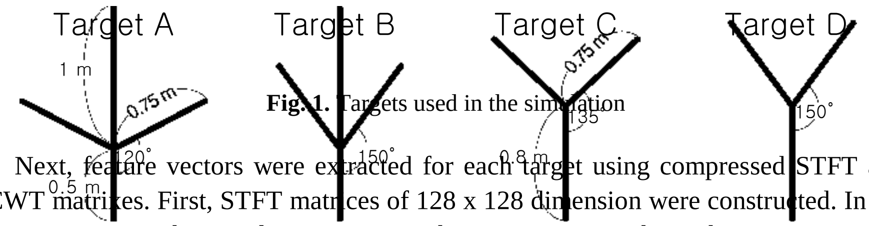

Fig. 1. Targets used in the simulation

Next, feature vectors were extracted for each target using compressed STFT and CWT matrices. First, STFT matrices of 128 x 128 dimension were constructed. In the STFT process, the window size was chosen as 15*ns*. Then, the matrices were compressed to 8 x 8 = 64 dimensions so that they could be effectively used as the input of the MLP neural network classifier. Unlike in the case of the STFT, the time span of CWT was divided into the early-time ($0 < t < t_L$) and late-time ($t > t_L$) stages, with $t_L = 10ns$. The dimensions during early and late-time stages were compressed to 4 x 8 and 8 x 4, respectively. Therefore, the final feature vector had 32 + 32 = 64 dimensions with the CWT.

Then, the targets were classified using an MLP neural network with two hidden layers [2]. The number of neurons in the first hidden layer was chosen to be half of the feature vector dimension, and that in the second hidden layer was chosen as one-third of that in the first hidden layer. We obtained the feature vectors at aspect angles of 0°~150° for each target. Aspect angles for the training data are from 1° to 149° with a 2° increment, and those for the test data are from 0° to 150° with a 2° increment. Therefore, we have 75 data sets for training, and 76 data sets for testing for each target. White Gaussian noise at a given SNR was also added to the original signal of all targets. The noisy signal was used for training to make the classifier robust to noise [3]. To guarantee the classifier performance, we trained it until the mean square error (MSE) was 10^{-5}. In addition, we performed 100 Monte Carlo simulations to enhance the reliability of the simulation.

Table 1. The wire target classification percentages and its standard deviation (in parenthesis) for various receiver positions of the bistatic radar

(a) Using STFT

Location of Tx and Rx	SNR [dB]				
	0	5	10	15	20
Tx=0°, Rx=15°	53.4 (2.5)	72.9 (2.0)	84.3 (1.7)	91.7 (1.3)	96.0 (1.0)
Tx=0°, Rx=30°	56.9 (2.4)	73.7 (2.2)	84.1 (1.7)	92.8 (1.4)	95.1 (1.0)
Tx=0°, Rx=45°	57.5 (2.4)	72.1 (2.3)	86.0 (1.9)	92.7 (1.4)	96.6 (0.8)
Tx=0°, Rx=60°	62.9 (2.3)	81.8 (1.7)	91.7 (1.2)	97.4 (0.7)	98.6 (0.6)
Tx=0°, Rx=75°	66.2 (2.0)	83.4 (1.6)	93.0 (1.1)	96.6 (0.8)	98.8 (0.5)
Tx=0°, Rx=90°	70.9 (2.0)	86.2 (1.4)	92.0 (1.1)	96.5 (0.8)	98.2 (0.7)
Tx=0°, Rx=105°	68.1 (2.1)	87.2 (1.6)	94.8 (1.0)	97.1 (0.8)	98.1 (0.7)
Tx=0°, Rx=120°	69.3 (2.2)	86.4 (1.5)	93.4 (1.1)	96.8 (0.7)	97.6 (0.6)
Tx=0°, Rx=135°	64.5 (2.5)	84.2 (1.6)	94.3 (1.0)	97.2 (0.6)	97.9 (0.6)
Tx=0°, Rx=150°	70.8 (2.6)	87.6 (2.1)	95.5 (0.8)	98.2 (0.5)	99.0 (0.4)
Tx=0°, Rx=165°	67.0 (2.7)	85.6 (1.5)	94.8 (1.0)	97.3 (0.6)	98.7 (0.4)

(b) Using CWT

Location of Tx and Rx	SNR [dB] 0	5	10	15	20
Tx=0°, Rx=15°	74.7 (1.8)	89.1 (1.5)	96.7 (1.0)	98.6 (0.6)	99.5 (0.3)
Tx=0°, Rx=30°	75.2 (1.9)	89.4 (1.4)	96.4 (0.9)	98.5 (0.4)	99.5 (0.3)
Tx=0°, Rx=45°	71.3 (2.3)	89.3 (1.4)	95.9 (0.8)	98.7 (0.5)	99.6 (0.3)
Tx=0°, Rx=60°	77.0 (2.0)	92.1 (1.3)	97.9 (0.7)	99.2 (0.4)	99.5 (0.2)
Tx=0°, Rx=75°	83.1 (1.8)	94.2 (1.2)	98.6 (0.5)	99.4 (0.3)	99.5 (0.2)
Tx=0°, Rx=90°	85.9 (1.5)	95.6 (1.0)	99.3 (0.4)	99.6 (0.3)	99.8 (0.1)
Tx=0°, Rx=105°	83.1 (2.2)	95.1 (0.9)	98.4 (0.6)	99.4 (0.3)	99.7 (0.2)
Tx=0°, Rx=120°	80.5 (2.0)	95.2 (0.9)	97.4 (0.6)	99.2 (0.3)	99.4 (0.2)
Tx=0°, Rx=135°	80.6 (2.0)	94.7 (1.2)	98.1 (0.6)	99.0 (0.3)	99.3 (0.2)
Tx=0°, Rx=150°	83.6 (2.2)	93.9 (1.1)	98.8 (0.5)	99.4 (0.3)	99.4 (0.3)
Tx=0°, Rx=165°	81.5 (2.1)	94.3 (1.1)	98.0 (0.5)	98.7 (0.3)	99.1 (0.2)

Table 1(a) and Table 1(b) show the target classification percentages and standard deviation (in parenthesis) for various positions of the bistatic radar receiver using the STFT and CWT, respectively. The simulation results indicate that regardless of the receiver position, the target classification performance using the CWT feature vector is better than that using the STFT feature vector. The optimum location of the CWT feature vector is identified as the transmitter and receiver at 0° and 90°, respectively. The optimum location of the STFT feature vector, on the other hand, is the transmitter and receiver at 0° and 150°, respectively. These results can be changed if we use other types of targets or other feature extraction techniques. As the target scattering mechanisms are very complex, it is very difficult to analyze why this combination of angles works best. But, if the targets of interest and feature extraction methods are determined, we can extract the optimum locations of transmitter and receiver for bistatic radar classification using the above process at any case.

4 Conclusions

In this paper, target classification performance using bistatic scattering field for four different wire targets is analyzed. The compressed STFT and CWT time-frequency techniques were used for feature vector extraction from the bistatic scattering field of each target, and an MLP neural network was used as a classifier.

For CWT feature vector, the optimum location of the transmitter and receiver were found to be at 0° and 90° for wire targets. The optimum location for the STFT feature vector, on the other hand, is the transmitter and receiver at 0° and 150° for wire targets.

Consequently, we can decide where the transmitter and receiver should be located in the bistatic radar when the targets, operating frequency and feature extraction techniques are determined.

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