Radar Waveform Design for Extended Random Target Model with Random Pose Angle Parameters

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***Abstract*— A radar waveform for target classification task is designed based on an extended target model since the extended target model is essential for target identification. One of the known algorithms for classification waveform is based on spectral variance, and its advantages have been verified well in [1][2][3]. We improved the waveform by deriving the lower bound of the information measure since a waveform is optimized by maximizing the information measure [4]. In this paper, we extend the two radar waveform algorithms with random pose angle parameters. The random pose angle information enables us to define the more realistic random target model since the three-dimensional target features are differently captured depending on radar illumination angles. We also compare the performance of the various waveform algorithms under the extended target model with random pose angle parameters.**

1. Introduction

A classification waveform algorithm optimized for target classification problem was introduced by defining mutual information based on energy spectral variance (MIESV) across the transfer functions of the various target hypotheses in [1][2][3]. The energy spectral variance (ESV) means a statistical variance or difference among the given target transfer functions. We enhanced the waveform by developing the lower bound of MIESV (LBM) in [4]. LBM waveform design method is derived based on both deterministic target model and random target model. In this paper, we focus on the random target model and generalize the target model with random pose angle parameters.

2. Conventional System Model and Waveform Design Algorithms

As an extended target model for a specific target j, we consider the similar stochastic system model with [2][3] as follows.

$$y(t) = w(t) * h_j(t) + n(t)$$

where $*$ means a convolution operation, a target hypothesis index $j = 1, 2, \ldots, \mathcal{H}$, $w(t)$ is a finite-energy waveform with duration T, $n(t)$ is the zero mean receiver noise process with power spectral density(PSD) $P_n(f)$ and the random target $h_j(t)$ is a wide-sense stationary process with PSD $S_h(f)$. For a finite-duration stochastic target model, we adopt a finite target model $g_j(t) = a(t)h_j(t)$ where $a(t)$ is a rectangular window function of duration T [3]. Now, we derive a frequency-domain system model based on a finite stochastic process model as follows.

$$\mathbf{y}(f) = \mathbf{w}(f)\mathbf{g}_j(f) + \mathbf{n}(f)$$

where $j = 1, 2, \ldots, \mathcal{H}$ and $f = 1, 2, \ldots, \mathcal{L}$. In a vector and matrix form, the measurement model becomes

$$\mathbf{y} = \mathbf{W}\mathbf{g}_j + \mathbf{n}$$

where $j = 1, 2, ..., \mathcal{H}$, $\mathbf{W}$ is a diagonal matrix with entries $\mathbf{w}(1), \mathbf{w}(2), \ldots, \mathbf{w}(\mathcal{L})$ and $\mathcal{L}$ is the length of observation vector $\mathbf{y}$, target vector $\mathbf{g}_j$, and noise vector $\mathbf{n}$. $\mathcal{H}$ is the total number of target classes which we need to classify. For a random target model, $\mathbf{g}_j$ is a finite-energy process with zero-mean [3]. Based on the stochastic system model, MIESV and LBM waveform optimization procedures are as follows [4].

$$\max T_y \int_B \ln\left[1 + \frac{|\mathbf{w}(f)|^2 S_R(f)}{T_y P_n(f)}\right] df$$
$$\text{subject to} \int_{\mathrm{B}} |\mathrm{w}(\mathrm{f})|^2 \mathrm{df} \le \mathrm{E_w}$$

where $S_R(f) = \sum_{j=1}^{\mathcal{H}} P(H_j)\sigma^2_{\mathbf{g}_j}(f) - \left|\sum_{j=1}^{\mathcal{H}} P(H_j)\sqrt{\sigma^2_{\mathbf{g}_j}(f)}\right|^2$ and $\sigma^2_{\mathbf{g}_j}(f)$ is the spectral energy of the j^{th} target.

$$\max \sum_{j=1}^{\mathcal{H}} P(H_j)\left\{T_y \int_B \ln\left[1 + \frac{|\mathbf{w}(f)|^2\{\sigma^2_{\mathbf{g}_j}(f) - \mu_R(f)\}}{T_y P_n(f)}\right] df\right\}$$
$$\text{subject to} \int_{\mathrm{B}} |\mathrm{w}(\mathrm{f})|^2 \mathrm{df} \le \mathrm{E_w}$$

where $\mu_R(f) = \left|\sum_{j=1}^{\mathcal{H}} P(H_j)\sqrt{\sigma^2_{\mathbf{g}_j}(f)}\right|^2$. $P(H_j)$ is the probability of j^{th} hypothesis or the probability that an j^{th} target presents. The mutual information is maximized with respect to waveform vector under given waveform energy constraint $\int_B |w(f)|^2 df \le E_w$. The MIESV waveform optimization is simply done by a water-filling method, and The LBM waveform optimization is performed by an iterative water-filling method.

3. Waveform Design with Pose-angle Parameters

For a practical radar system for target identification, we need to consider the multiple pose angle of three-dimensional target since one specific target has a typical stereoscopic shape which generates different radar cross sections depending on radar illumination directions as shown in Figure 1. Thus, radar

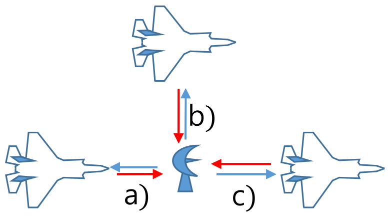

Fig. 1. Multiple pose angles of a target. In this case, three target signatures are considered for one target

target transfer vector is extended to $\mathbf{g}_{ij}$ for $i = 1, 2, \ldots, \mathcal{V}$ and $j = 1, 2, \ldots, \mathcal{H}$. The pose angle index i depends on the specific target hypothesis index j since the j^{th} target class is characterized by the $\mathcal{V}$ number of transfer vectors. The pose angle information of a target enables us to build a more realistic random target model. However, it acts as a nuisance parameter in the final classification task since the pose angle information adds more randomness to the target model. In another point of view, if we can estimate the pose angle parameters rather precisely, the randomness by the pose angle parameters can be reduced.

Figure 1 shows three different echoes from three different pose angles of one target. It is assumed that the target signatures of the three pose angles are independent each other and a radar waveform should be optimized by the increased number of target hypotheses. For example, eight target hypotheses are required for four target models with two pose angles.

Therefore, MIESV with pose angle parameters becomes

$$MIESV = T_y \int_B \ln \left[1 + \frac{|\mathbf{w}(f)|^2 S_R(f)}{T_y P_n(f)} \right] df$$

where
$S_R(f) = \sum_{i=1}^{\mathcal{V}} \sum_{j=1}^{\mathcal{H}} P_{ij} \sigma^2_{\mathbf{g}_{ij}}(f) - \left| \sum_{i=1}^{\mathcal{V}} \sum_{j=1}^{\mathcal{H}} P_{ij} \sqrt{\sigma^2_{\mathbf{g}_{ij}}(f)} \right|^2,$
$P_{ij} = P(V_i \cap H_j) = P(V_i|H_j)P(H_j)$, and P_{ij} is the probability that the radar system capture the i^{th} pose angle signature of j^{th} target. $P(V_i)$ is the probability that an i^{th} pose angle is selected among the $\mathcal{V}$-number of pose angles. On the other hand, LBM with pose angle parameters becomes

$$\text{LBM} = \sum_{i=1}^{\mathcal{V}} \sum_{j=1}^{\mathcal{H}} P_{ij} \left\{ T_y \int_B \ln \left[1 + \frac{|\mathbf{w}(f)|^2 \{\sigma^2_{\mathbf{g}_{ij}}(f) - \mu_R(f)\}}{T_y P_n(f)} \right] df \right\}$$

where $\mu_D(f) = \left| \sum_{i=1}^{\mathcal{V}} \sum_{j=1}^{\mathcal{H}} P_{ij} \mathbf{g}_{ij}(f) \right|^2$.

4. Simulation Result

In this section, we present simulation results of three waveform design algorithms such as wideband, MIESV, and LBM based on the extended random target model with pose angle parameters. We evaluate the percentage of correct detection in determining the true target transfer function for three different waveforms and compare their performances in Figure 2. The first waveform is a wideband waveform having a flat energy distribution across the transmission band,

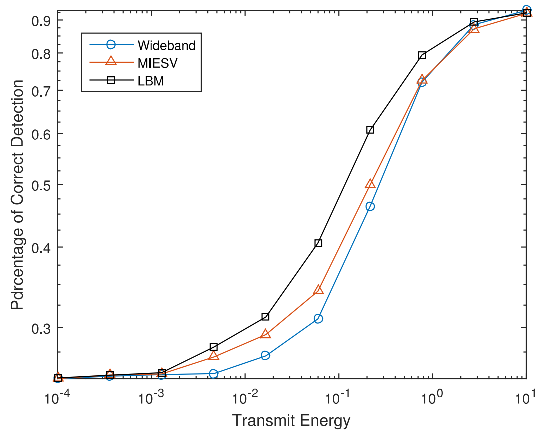

Fig. 2. Performance comparison of various waveform design methods in case of 40 tap waveform with 2 pose angles

and the second waveform is an MIESV waveform. The last waveform is the LBM waveform. The number of target hypotheses is $\mathcal{H} = 4$, and the number of pose angles for each target is $\mathcal{V} = 2$. The waveform dimension $\mathcal{L}$ is 40 for the random target simulation. The measurement noise power is normalized to $\sigma^2 = 1$, the waveform energy allocation varies from 10^{-4} to 10^{1} energy units, and the percentage of correct detection is calculated over 20,000 Monte Carlo trials. From the results, LBM waveform shows the best performance among Wideband, MIESV, and LBM waveforms.

5. Conclusion

We enhanced a radar random target model with pose angle parameters and updated two waveform optimization algorithms based on the enhanced model. Stereoscopic information of a radar target can be considered by the pose angle information. In a simulation, LBM algorithm which we proposed in [4] still shows the best performance. We will take advantage of the pose angle information to get some diversity gain in MIMO radar configuration in our next paper.

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References

[1] N. A. Goodman, P. R. Venkata, and M. A. Neifeld, "Adaptive waveform design and sequential hypothesis testing for target recognition with active sensors," *IEEE Journal of Selected Topics in Signal Processing*, vol. 1, no. 1, pp. 105–113, Jun. 2007.

[2] R. A. Romero and N. A. Goodman, "Waveform design in signal-dependent interference and application to target recognition with multiple transmissions," *IET Radar, Sonar Navigation*, vol. 3, no. 4, pp. 328–340, Aug. 2009.

[3] R. A. Romero, J. Bae, and N. A. Goodman, "Theory and application of snr and mutual information matched illumination waveforms," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 47, no. 2, pp. 912–927, Apr. 2011.

[4] H. Kim, C. Lee, and S. Yang, "Improved waveform design for radar target classification," *Submitted to Electronics Letters*, 2016.