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A divergence mean-based geometric detector with a pre-processing procedure

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ABSTRACT

This paper proposes a divergence mean-based geometric detector to deal with the problem of target detection in a clutter with the limited sample data. In particular, a covariance matrix is used to model the correlation of sample data in each cell in one coherent processing interval. This modeling method can avoid the poor Doppler resolution as well as the energy spread of the Doppler filter banks result from the fast Fourier transform. Moreover, a pre-processing procedure, conceived from the philosophy of the bilateral filtering in image denoising, is proposed and combined within the geometric detection framework. As the pre-processing procedure acts as the clutter suppression, the performance of geometric detector is improved. Numerical experiments and real clutter data are given to validate the effectiveness of our proposed method.

1. Introduction

Improving the performance of target detection in a clutter is very important for a radar system. However, the classical fast Fourier transform (FFT) based constant false alarm rate (CFAR) detector [1] usually suffer from severe performance degradation with the limited sample data. This is because, the Doppler resolution is poor and the energy of the Doppler filter banks spreads, when the FFT is used to model the correlation of sample data. To address these problems, Barbaresco employed the structure of Riemannian manifold, and has proposed a generalized CFAR technique on a Riemannian manifold of Hermitian positive-definite (HPD) matrices. This method was named as the Riemannian mean-based geometric detector [2]. In this detector, the pulse data $\boldsymbol{z}$ is modeled by a Gaussian random process with zero mean, and then the information of target is represented by an HPD matrix $\boldsymbol{R}_i$. The detection statistic is defined as the distance between the HPD matrix $\boldsymbol{R}_D$ of cell under test and the mean matrix $\bar{\boldsymbol{R}}$ calculated by the matrices of reference cells. The mean matrix denotes the clutter power level. Finally, the decision is made by comparing the statistic in each cell with an adaptive threshold γ. It can be referred to Fig. 1. As this detector takes the structure of HPD matrix space into account, it can be viewed as a geometric detector.

In this geometric detector, the sample data in each range cell in one CPI is modeled as an HPD matrix. The geometric metric is derived according to this parameterization [2,3]. On the basis of the metric, the existence and uniqueness of geometric mean had been proven in [4]. The geometric detector has been used to monitor the turbulence of a plane [5–7], target detection in coastal X-band and HF surface wave radars [2,3]. Many experimental results have shown that the performance of geometric detector outperforms the FFT-CFAR [3].

The Riemannian mean-based geometric detector and the classical FFT-CFAR detector are of similar schemes under the CFAR formulation. The main difference between the geometric detector and the FFT-CFAR detector in the following three aspects: 1) the model for the correlation of data is an HPD matrix, instead of the FFT coefficient; 2) the distance metric utilized is the geometric measure, and not the Euclidean distance; and 3) the average value of HPD matrices is the geometric mean, rather than the arithmetic average. These differences imply that the geometric detector performs on the HPD matrix space, in other words, the different geometry considered in detection. Furthermore, as the geometric detection method is performed on the HPD covariance matrix space, in this sense, the geometric method can be seemed as the

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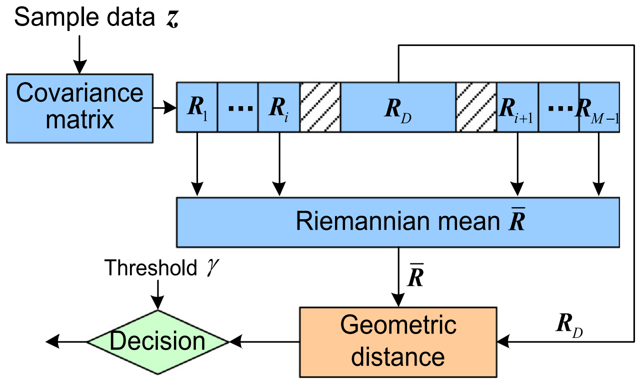

Fig. 1. Riemannian mean-based geometric detector [2].

covariance matrix-based geometric detection. Under the generalized likelihood ratio test (GLRT), there are many covariance matrix-based algorithms, such as the Kelly's GLRT detector [8], the adaptive matched filter detector [9], and the normalized matched filter detector [10]. In particular, in [11–13], the authors exploit the priori information about the surrounding environment for estimating the covariance matrix to achieve a significant performance improvement. Another example is provided in [14], the Bayesian approach is employed to assume a suitable distribution about the unknown clutter covariance matrix, and similar methods also are found in [15]. The common goals of these detection algorithms are to attain a suitable covariance matrix in nonhomogeneous non-Gaussian clutter, and to improve the detection performance. The decisions about the presence and absence of a target with respect to these methods are made by Neyman-Pearson Lemma according to compare the value of test statistic with a threshold, which is set by fixing the false alarm probability at a certain level while maximizing the probability of detection. These covariance matrix–based algorithms do not consider the intrinsic structure embedding in covariance matrix space, and are based on the Neyman-Pearson criterion. Therefore, these methods are totally different from the geometric detection method which is based upon the properties of the Gaussian processes instead of the Neyman–Pearson Lemma.

Many metrics can be used to measure the closeness between any two points on the Riemannian manifold of HPD matrices. Different measurements can reflect different structures of this space. Many divergences can be used as measurements. Mentioned a few, the square loss is used to measure the distance between the two states in the regression; the Bhattacharyya divergence has employed to medical image segmentation [16,17]; and the Kullback-Leibler (KL) divergence has been widely used to measure the information difference between two probability distributions [18]. These metrics have achieved good results in many applications. In our previous work [19], we have studied a geometric detection method based on KL divergence. Experiments have shown that its performance outperforms the traditional FFT-CFAR detector.

In this paper, we explore the geometric detector base on different metrics. In particular, the Log-Euclidean distance [20], the Bhattacharyya divergence [21], and the Hellinger distance [22] are used as replacements of the Riemannian distance in the geometric detector. Based on the three metrics, the Log-Euclidean mean [23], the Bhattacharyya mean [16], and the Hellinger mean [22] of a finite set of HPD matrices are derived. As a result, a divergence mean-based geometric detector is developed. Moreover, we propose a weighted average filter which is combined within the geometric detector. This filter is conceived from the philosophy of the bilateral filtering in image denoising [24]. As this filter acts as a clutter suppression procedure, the detection performance can be improved.

The rest of this paper is organized as follows. In Section 2, we give a description about the signal model and signal manifold. In Section 3, the Riemannian geometry of space of HPD matrices and the divergence means are presented. The divergence mean-based geometric detector is developed in Section 4. Then, we evaluate the performances of the divergence mean-based geometric detector as well as the Riemannian mean-based geometric detector and the FFT-CFAR detector by simulated data and real clutter data in Section 5. Finally, conclusion is provided in Section 6.

1.1 Notation

Here are some notations for the descriptions of this article. A scalar x is denoted using the math italic. A matrix $\boldsymbol{A}$ and a vector $\boldsymbol{x}$ are noted as uppercase bold and lowercase bold, respectively. The conjugate transpose of matrix $\boldsymbol{A}$ is denoted as $\boldsymbol{A}^H$. $tr(\boldsymbol{A})$ is the trace of matrix $\boldsymbol{A}$. $\det(\boldsymbol{A})$ is the determinant of matrix $\boldsymbol{A}$. $\boldsymbol{I}$ denotes the identity matrix. The set of all n-dimensional vectors is noted by $\mathbb{C}(\ n)$. $\mathbb{H}(n)$ is the set of all $n \times n$ Hermitian matrices. $\|\boldsymbol{A}\|_F$ denotes the F-norm of matrix $\boldsymbol{A}$. $\mathbb{P}(n)$ is the space of all $n \times n$ HPD matrices. Finally, $\mathbb{E}(\cdot)$ denotes the statistical expectation.

2. Signal model and signal manifold

The radar usually sends several pulses to a moving target, and receives the return data which contains the phase information of this target. A certain model is used to capture the Doppler of target. In this paper, the Doppler is represented as the correlation of data $\boldsymbol{z} = \{z_1, z_2, \ldots, z_n\}$, and is modeled as a multivariate Gaussian process with zero mean, $\boldsymbol{z} \sim CN(\boldsymbol{0}, \boldsymbol{R})$ [2],

$$\boldsymbol{p}(z|\boldsymbol{R}) = \frac{1}{\pi^n \det(\boldsymbol{R})} \exp\{-\boldsymbol{z}^H \boldsymbol{R}^{-1} \boldsymbol{z}\} \tag{1}$$

here, the matrix $\boldsymbol{R}$ is an HPD matrix, and it can be computed as [2],

$$\boldsymbol{R} = \mathbb{E}[zz^H] = \begin{bmatrix} r_0 & \bar{r}_1 & \cdots & \bar{r}_{n-1} \\ r_1 & r_0 & \cdots & \bar{r}_{n-2} \\ \vdots & \ddots & \ddots & \vdots \\ r_{n-1} & \cdots & r_1 & r_0 \end{bmatrix}, \tag{2}$$
$$r_k = \mathbb{E}[z_i \bar{z}_{i+k}], \quad 0 \le k \le n-1, \quad 0 \le i \le n-1$$

where r_k denotes the correlation coefficient of pulse data, and $\bar{r}_i$ is the complex conjugate of r_i. As there is not enough sample data to compute the statistical expectation $\mathbb{E}[z_i \bar{z}_{i+k}]$, according to the ergodicity, it can be calculated by a finite time serial,

$$\hat{r}_k = \frac{1}{n-k} \sum_{j=0}^{n-1-k} z_j \bar{z}_{j+k}, \qquad 0 \le k \le n-1 \tag{3}$$

The pulse data $\boldsymbol{z} = \{z_1, z_2, \ldots, z_n\}$ in each cell in one CPI is modeled by Eqs. (1) and (2), and represented by an HPD matrix $\boldsymbol{R}$. The pulse data $\boldsymbol{z}$ is staying in the Euclidean space, and the HPD matrix $\boldsymbol{R}$ is viewed as a point in the manifold. Through this parameterization, the data $\boldsymbol{z}$ is transformed into an n dimensional non-liner manifold space,

$$\psi : \mathbb{C}(n) \to \mathbb{P}(n), \quad z \to \boldsymbol{R} \in \mathbb{P}(n) \tag{4}$$

Here $\mathbb{P}(n)$ forms a differentiable Riemannian manifold [25] with non-positive curvature [26,27]. Through this modelling for the radar echo, the target detection should be performed in the manifold. In particular, the structure of matrix space can be considered. The manifold $\mathbb{P}(n)$ is a symmetric space [28], and more presentations can be found in [29].