Multiscan Recursive Bayesian Method for Parameter Estimation of Spatially-varying Sea Clutter Models

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***Abstract*—Large-scene sea clutter exhibits spatially-varying power and non-Gaussianity due to varying grazing angle and sea state, which leads to the lack of data with consistent statistical property, called spatially small-sample (SSS) problem. Therefore, compound-Gaussian model with spatially-varying texture is introduced to characterize large-scene sea clutter. However, existing methods of sea clutter parameter estimation, including moment-based, maximum likelihood and explicit bipercentile estimators, lose their estimation efficiencies with the SSS problem. In this study, a multiscan recursive Bayesian (MRSB) method is proposed to deal with the estimation problem of spatially-varying sea clutter parameters. This method is constructed by transforming scanning data in frames to the prior information of parameters in order to cover the shortage of sample number. The MRSB method not only improves the parameter estimation property of spatially-varying sea clutter due to the performance assessment with clutter data, but also starts a new mode of radar, that is, radar remembers all information and no data.**

Keywords*—*Large-scene sea clutter; spatially small-sample problem; spatially-varying compound-Gaussian model; explicit bipercentile estimators; multiscan recursive bayesian method

I. INTRODUCTION

Advanced radar detection schemes necessitate accurate parameter estimation methods of the large-scene clutter models in order to update the false alarm rate. Compound-Gaussian models are often used to characterize heavy-tailed clutter distributions in high-resolution radar, which are expressed as the product of speckle component and a positive texture component. There exist three types of textures to adapt sea clutter to different detection circumstances: the Gamma texture relates to the K-distributed amplitude model [1], the inverse Gamma texture exports the famous generalized Pareto (GP) intensity model [2], and the inverse Gaussian texture educes a recent amplitude model, referred to as the CG-IG model [3].

The GP-distributed model attains better goodness-of-fit in most cases by statistical analysis of X-band high-resolution sea clutter [4,5]. The parameters of GP distribution can be estimated by the moment-based and maximum likelihood (ML) estimators [2] and the method of log-cumulants (MoLC) [6]. Considering that unavoidable outliers severely interfere with detection and parameter estimation in real radar environments [7,8], which makes all estimators above lose their estimation precision, an explicit bipercentile (BiP) estimator was given in [9]. It is outliers-robust and its performance is comparable with other estimators in the case without outliers. Particularly, all estimators aforementioned can achieve specific parameter estimation of GP-distributed clutter with the assumption of enough samples. However, large-scene sea clutter exhibits spatially-varying power and non-Gaussianity due to varying grazing angle and sea state, which leads to the lack of data with consistent statistical property, called spatially small-sample (SSS) problem. It degrades performances of all estimators above heavily.

In this paper, compound-Gaussian model with spatially-varying texture is introduced to characterize large-scene sea clutter. All three existed texture types of compound-Gaussian models are available. Here we choose the inverse Gamma texture which exports the spatially-varying generalized Pareto (SV-GP) model. To achieve the parameter estimation of SV-GP model with the SSS problem, a multiscan recursive Bayesian (MRSB) method is proposed. For the slowly-varying feature among adjacent scanning frames on fixed spatial positions, its parameter estimation of current frame is constructed by data of two parts, including the small samples of current frame and the prior information of parameters transformed from scanning data in previous multiple frames, which is supposed to cover the shortage of sample numbers. The MRSB method not only improves the parameter estimation property of SV-GP model proved by experiments, but also starts a new work mode of radar, that is, radar remembers all information and no data.

This paper is organized as follows. Section 2 briefly reviews the generalized Pareto clutter model and corresponding effective methods of parameter estimation. In Section 3, we present the derivation of spatially-varying compound-Gaussian models for large-scene sea clutter and the multiscan recursive Bayesian method to deal with parameter estimation problem of new models. In Section 4, we handle the performance assessment of the structure with simulated sea clutter data, while conclusions and hints for future research are listed in Section 5.

II. Review of Clutter Model and Parameter Estimation Methods

A. Compound-Gaussian Clutter Model

In high-resolution maritime radar, compound-Gaussian models are often used to characterize heavy-tailed clutter distributions, which are constructed by the product of speckle component and a positive texture component as

$$\boldsymbol{c} = \sqrt{\tau}\boldsymbol{u} \tag{1}$$

where the speckle $\boldsymbol{u}$ is a zero-mean complex Gaussian random variable and the texture τ is a positive random variable. The inverse Gamma distributed texture is considered here, that is, $1/\tau$ follows the Gamma distribution,

$$p(\tau;\nu,b) = \frac{1}{b^{\nu}\Gamma(\nu)}\tau^{-(\nu+1)}\mathrm{e}^{-1/(b\tau)}, \tau > 0; \nu, b > 0 \tag{2}$$

ν and b are the shape and scale parameters while $\Gamma(\bullet)$ refers to the Gamma function. Particularly, the compound-Gaussian model in (1) leads to the complex multivariate generalized Pareto (GP) distributed clutter model. The amplitude $z=|\boldsymbol{c}|$ has a probability density function (PDF) and a cumulative distribution function (CDF) [2],

$$f(z;\nu,b) = \frac{2\nu bz}{\left(1+bz^2\right)^{\nu+1}}; F(z;\nu,b) = 1 - \frac{1}{\left(1+bz^2\right)^{\nu}}, z > 0 \tag{3}$$

The statistical analysis of existed X-band high-resolution sea clutter has shown that the GP-distributed model in (3) attains better goodness-of-fit in most cases than the K-distributed and the CG-IG model [4,5]. However, large-scene sea clutter exhibits spatially-varying power and non-Gaussianity due to varying grazing angle and sea state. It suffers from heavy loss in characteristic description when GP distribution is used to characterize sea clutter with spatially-varying property. Therefore, compound-Gaussian model with spatially-varying texture is introduced in this paper later.

B. Parameter Estimation Methods of GP Distribution

The parameters of the GP distribution can be estimated by the moment-based and maximum likelihood (ML) estimators [2] and the method of log-cumulants (MoLC) [6]. Particularly, the moment-based estimators can only work in a restricted range of shape parameter. Since the sample moments always exist, we will fail to realize that a wrong result is given when the shape parameter of data falls outside its working range. The ML estimator achieves high precision close to the Cramer-Rao bound (CRB) [2] but its scale parameter is obtained by solving a nonlinear equation which is difficult to implement stably and fast. The MoLC estimator [6] can work fast but suffers from loss in performance. Considering that unavoidable outliers severely interfere with detection and parameter estimation in real radar environments [7,8], which makes all estimators above lose their estimation precision, an explicit bipercentile (BiP) estimator was given in [9]. It is outliers-robust and its estimate accuracy is good. Particularly, a review of the outliers-robust BiP estimator is provided here.

According to the amplitude CDF in (3), two percentiles can cooperate to compute the scale and shape parameters [8], i.e., for $0<\alpha<\beta<1$,

$$\left(1+bz_{\alpha}^2\right)^{\nu} = 1/(1-\alpha); \left(1+bz_{\beta}^2\right)^{\nu} = 1/(1-\beta). \tag{4}$$

where z_α and z_β refer to the α-percentile and β-percentile of the random variable z, respectively.

Set $q=\ln(1-\beta)/\ln(1-\alpha)>1$, the ratio of two equations in (4) exports an expression unrelated to the scale parameter b as

$$\frac{z_\beta^2}{z_\alpha^2} = \frac{\left(1/(1-\beta)\right)^{1/\nu}-1}{\left(1/(1-\alpha)\right)^{1/\nu}-1} = \frac{u^q-1}{u-1} \tag{5}$$

where $u=(1/(1-\alpha))^{1/\nu}$ refers to an auxiliary variable which is determined by both q and the ratio z_β/z_α. Equation (5) has been proved having a unique positive solution, while the solution is given by the iterative procedure in [9] as

$$\begin{aligned} &u_0 \in (1,+\infty), u_{k+1} = \left(\frac{z_\beta^2}{z_\alpha^2}(u_k-1)+1\right)^{1/q}, u = \lim_{k\to\infty} u_k, \\ &\nu = -\frac{\ln(1-\alpha)}{\ln(u)}, b = \frac{u-1}{z_\alpha^2}. \end{aligned} \tag{6}$$

When the ratio q is a positive integer, equation (5) can be reshape into a (q-1)-degree polynomial equation. The root of (5) is supposed to be computed analytically by the root formulae of the algebraic polynomials when q is a positive integer no more than 5 [10],

$$\begin{aligned} &u = z_\beta^2/z_\alpha^2 - 1, \quad \text{when } q=2; \\ &u = \sqrt{z_\beta^2/z_\alpha^2 - 3/4} - 1/2, \quad \text{when } q=3; \\ &u = \sqrt[3]{\sqrt{\psi^2+8/3^6}+\psi} - \sqrt[3]{\sqrt{\psi^2+8/3^6}-\psi} - 1/3, \\ &\psi = 0.5\, z_\beta^2/z_\alpha^2 - 10/3^5, \quad \text{when } q=4, \\ &\nu = -\frac{\ln(1-\alpha)}{\ln(u)}, b = \frac{u-1}{z_\alpha^2}. \end{aligned} \tag{7}$$

When q=5, the explicit expressions are too lengthy to be listed.

The performance assessments in [9] showed that the BiP estimator in (6) and (7) achieves competitive performance with the FMoM and MoLC estimators in the cases without outliers. In the cases with outliers, the BiP estimator provides robust estimate while other estimators, even the most accurate ML estimator, fail to work. However, when it comes to the large-scene sea clutter which suffers performance loss from the lack of data with coincident statistical property, called spatially small-sample (SSS) problem, a modified estimator is urgent to be constructed.

III. SPATIALLY-VARYING SEA CLUTTER MODELS AND MULTISCAN RECURSIVE BAYESIAN METHOD

A. Spatially-varying Sea Clutter Models

For the maritime surveillance radars set in offshore areas, the characteristics of sea clutter vary with its spatial positions due to the complex sea circumstances and the volatile meteorological conditions. Therefore, samples in space with the same statistical property are severely scanty and the traditional compound-Gaussian clutter models with unitary characteristic will fail to describe the statistical property of sea clutter in this condition. Here, the spatially-varying sea clutter models based on the compound-Gaussian clutter models in (1) are proposed as a 4-dimensional variable

$$c(n;r,\theta,t)=\sqrt{\tau(r,\theta,t)}\,\boldsymbol{u}(n;r,\theta,t) \tag{8}$$

where the spatially-varying clutter samples are varying with the variables including the clutter pulse n, the radial distance r, the azimuth angle of radar θ and its scanning time t. The spatially-varying speckle $\boldsymbol{u}(n;\ r,\ \theta,\ t)$ is a complex Gaussian random variable and the spatially-varying texture $\tau(r,\ \theta,\ t)$ which does not vary with the clutter pulse n is a positive random variable with specific probability density distributions as

$$p(\tau;\nu(r,\theta,t),b(r,\theta,t))=\frac{\tau^{-(\nu(r,\theta,t)+1)}\mathrm{e}^{-1/(b(r,\theta,t)\tau)}}{b(r,\theta,t)^{\nu(r,\theta,t)}\,\Gamma(\nu(r,\theta,t))} \tag{9}$$

which is the extension of the Gamma texture in (2), while all the shape parameters $\nu(r,\ \theta,\ t)$ and scale parameters $b(r,\ \theta,\ t)$ are changing with both time and space, related to the variables r, θ and t.

Substituting (9) into (8), the spatially-varying GP-distributed (SV-GP) model is generated. Particularly, the PDF and the CDF of the SV-GP clutter amplitude $z=|\boldsymbol{c}|$ share the same expressions in (3) except that the shape and scale parameter ν and b are supposed to be displaced by the spatially-varying ones, $\nu(r,\ \theta,\ t)$ and $b(r,\ \theta,\ t)$.

B. Multiscan Recursive Bayesian Method

The SV-GP clutter model always suffers estimating performance loss from the lack of data with coincident statistical property, the spatially small-sample problem. In order to cover this shortage, the data cube Ω_l is proposed here as

$$\Omega_l(r_0,\theta_0)=\{c(n\,|\,r,\theta,s):(r,\theta)\in\Theta(r_0,\theta_0),s\in\{t,...,t-T\}\} \tag{10}$$

where $\Theta(r_0,\theta_0)$ refers to an area with the center point (r_0,θ_0), in which the clutter statistical property can be considered to be coincident with acceptable loss in performance. The variable T means that the clutter statistical property can be considered to be invariable in T scanning frames of radar. Particularly, the varying characteristics in space of parameters are related to the marine environment and the working condition of radar, in which the wide sea level can share the same parameters ν and b in among 10 km×10 km area while the offshore areas share the same parameters in much less range due to the complex marine environment. Besides, parameters with the varying characteristics in time can share the same value in scores of scanning frames because of the slow-varying property of radar's exposure scenarios. Besides, the current-frame data Ω_t is supposed to be expressed as

$$\Omega_t(r_0,\theta_0)=\{c(n\,|\,r,\theta,t):(r,\theta)\in\Theta(r_0,\theta_0)\} \tag{11}$$

In the view of the data cube, traditional parameter estimators of compound-Gaussian clutter models, including the BiP estimator of GP-distributed model in (6) and (7), are achieved based on the current-frame data $\Omega_t(r_0,\theta_0)$.

Due to the SSS problem in large-scene sea clutter, samples of $\Omega_t(r_0,\theta_0)$ are so scarce that the estimated performances of all the traditional estimators will be degraded heavily. Therefore, a multiscan recursive Bayesian (MRSB) method is proposed here. It completes parameter estimation progress via a combination of the current-frame data $\Omega_t(r_0,\theta_0)$ and the prior information of parameters obtained by the data in previous scanning frames. Particularly, the MRSB estimator can be expressed as

$$\hat{\Phi}_t(r_0,\theta_0)=MRB\{\Omega_t(r_0,\theta_0)\,|\,\hat{\Phi}_{t-1}(r_0,\theta_0)\} \tag{12}$$

where $\hat{\Phi}_t(r_0,\theta_0)=[\hat{\nu}_t(r_0,\theta_0),\hat{b}_t(r_0,\theta_0)]$ refers to a set of estimated value of shape and scale parameters in the t-*th* scanning frame. The using of parameter prior information $\hat{\Phi}_{t-1}(r_0,\theta_0)$ in the MRSB estimator covers the shortage of sample numbers to a great extent. It not only improves the parameter estimation property of spatially-varying sea clutter models, more importantly, it starts a new mode of radar, that is, radar remembers all information and no data.

IV. PERFORMANCE ASSESSMENT

The MRSB methods realize dynamic parameter estimation among multiple frames in spatially-varying sea clutter models. Considering that the spatially-varying sea clutter models derive from the compound-Gaussian clutter models, the MRSB methods are supposed to apply all the effective parameter estimators in traditional compound-Gaussian clutter models, except for its using of parameter prior information $\hat{\Phi}_{t-1}(r_0,\theta_0)$ in (12) to cover the shortage of sample numbers. Particularly, a forgetting factor $\xi\in[0,1]$ is used here to decide the proportion that the prior information $\hat{\Phi}_{t-1}(r_0,\theta_0)$ takes in the current-frame parameter estimation. If the radar detecting environment is varying slowly with space and time, the forgetting factor is supposed to be small to let radar forget the prior information in previous frames slowly, and vice versa.

A. Application of MRSB Method

Due to the effective goodness-of-fit of GP-distributed clutter model and the stable parameter estimating performance of its outliers-robust BiP estimator, an application of MRSB method based on the BiP estimator (MRSB-BiP) for the SV-GP distributed clutter model is constructed here.

Since the expressions of BiP estimator in (6) and (7) are established via two sample amplitude value z_α and z_β from the random variable $z=|c|$, the prior information $\hat{\Phi}_{t-1}(r_0,\theta_0)$ is supposed to be altered to effective clutter samples simulated via the SV-GP clutter model in (8) and spliced with the clutter data set of current scan $\Omega_t(r_0,\theta_0)$. Supposing the size of the current-frame data $\Omega_t(r_0,\theta_0)$ is M_t, the size of the sample data derived from $\hat{\Phi}_{t-1}(r_0,\theta_0)$ can be expressed by the forgetting factor ξ as

$$\hat{M}_{t-1}=\frac{1-\xi}{\xi}\cdot M_t \tag{13}$$

For instance, if the forgetting factor $\xi=0.1$, the overall sample size $N=M_t+\hat{M}_{t-1}$ is 10 times to the size of current-frame data $\Omega_t(r_0,\theta_0)$. Next, compute the amplitude of the N-sized clutter sample matrix and turn the matrix into an amplitude vector as $\boldsymbol{z}=[z_1, z_2, \dots, z_N]$. Finally, sorting the amplitude vector into an ascending one as $\boldsymbol{z}=[z_{(1)}, z_{(2)}, \dots, z_{(N)}]$, the α-percentile and β-percentile of the random variable z are supposed to be derived by

$$z_\alpha=z_{([N\alpha])},\ z_\beta=z_{([N\beta])} \tag{14}$$

where $[x]$ denotes the integer nearest to x. Substituting (14) into (6) and (7), the estimated parameters $\nu(r,\theta,t)$ and $b(r,\theta,t)$ from the MRSB-BiP estimator are designed easily and reliably here.

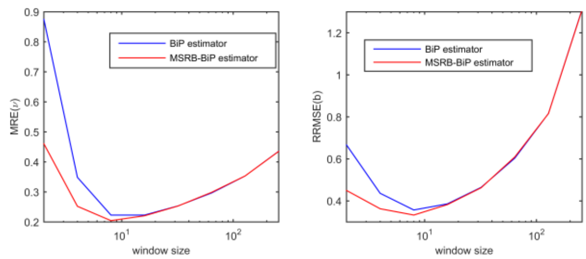
B. Performance Results

In order to reproduce the slowly spatially-varying characteristics of large-scene sea clutter, the pixel values of *Fig.1*(a) and *Fig.1*(b) with the size of 2048×1280 are used to simulate the shape parameter ν and the scale parameter b in proportion, respectively. Considering that the clutter tends to the Gaussian distribution as $\nu\to+\infty$ and the amplitude characteristics of clutter have little difference with large shape parameter [11], the maximum shape parameter here is fixed as $\nu=10$. Besides, the range of scale parameter b is defined as $b\in[1,5]$ proportionally because the sample power in real detection scene changes marginally. Set the pulse number $n=10$, a scan of clutter matrix $\boldsymbol{c}(n;\ r,\ \theta,\ t)$ with spatial variability and the size 2048×1280×10×1 is supposed to be simulated by (8) easily. Considering that parameters with the varying characteristics in time can share the same value in scores of scans, the multi-scan spatially-varying clutter matrices Ω_t with the scan number $t=1,2,\dots,35$, respectively, can be generated in the same way by (8). Due to the slowly-varying property of adjacent parameters in the underlying scene *Fig.1* and the form of MSRB method in (12), the clutter samples generated from 2048×1280 parameters in *Fig.1* are divided into small areas as $\Omega_t(r_0,\theta_0)$ before estimating processing. Importantly, a bigger window is arranged to cover the small one with the same center (r_0,θ_0) and implement the parameter estimation of the area $\Theta(r_0,\theta_0)$, shown as $\hat{\Phi}_t(r_0,\theta_0)$, in order to ensure the continuity of estimating results among adjacent area, namely blocking artifact.

(a) Shape parameter (b) Scale parameter

Fig.1 Simulated scene of spatially-varying parameters

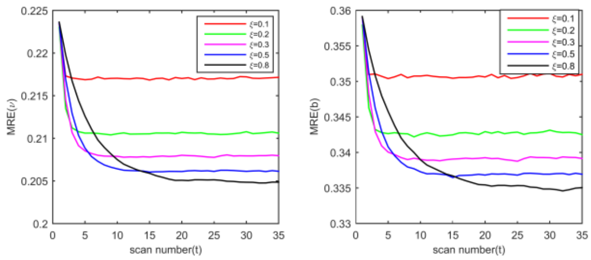
The size of window is an important factor for estimation accuracy and the optimal window size is related to the change rate of clutter parameters closely. Specifically, if the window size is too small, the estimation accuracy would be influenced due to the shortage of data samples, while the results would be unreliable if the window size is too big because the characteristics among non-neighboring spatial resolution cells are obviously different. Thus, the mean relative errors (MREs) of estimation results for both shape parameter and scale parameter are studied with the variation of the small window size in *Fig.2* and the size of the big window is regulated as 4 times to the small one with the same center reasonably. In the experiment, the size of the small window is increasing from 2×2 to 128×128, while the corresponding big window size is varying from 4×4 to 256×256. Besides, the forgetting factor ξ for the MSRB-BiP estimator is fixed as 0.1 and the scan number t is 35. In *Fig.2*, it can be seen that the MREs for both shape and scale parameters reduce with small window size and increase with large window size. Particularly, the optimal window size for both shape and scale parameters is 8×8 in the underlying clutter scene. Thus, the window size of all the simulated experiments below is fixed as 8×8. Besides, the MSRB-BiP estimator shows better estimation accuracy especially when the window size is small. This is because the samples are severely deficient for the BiP estimator when too small window is used, while the MSRB-BiP estimator can fix this problem via information application among multiple scans.



(a) MRE of shape parameter (b) MRE of scale parameter

Fig.2 MREs of parameters versus window size

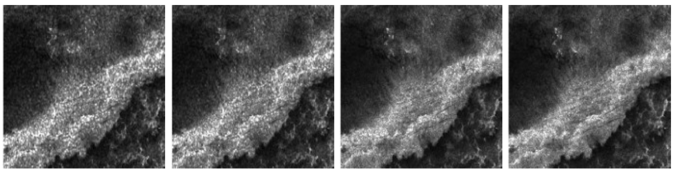
Besides, the forgetting factor ξ is also an important value for the estimation performance of the MSRB-BiP estimator. In *Fig.3*, the MREs for both the shape and scale parameters of the MSRB-BiP estimator are computed versus the increase of the scan number t with different values of the forgetting factor ξ. Particularly, the factor ξ is fixed as 0.1, 0.2, 0.3, 0.5, and 0.8. It can be seen that the MREs in all curves below decrease with the scan number and tend to be stable finally. With the increase of the forgetting factor ξ specifically, the stable MREs of both shape and scale parameters become smaller, which is because more data samples are used by this time, meanwhile the bigger scan number t is requisite in order to get the steady accuracy. Generally, the estimation error is supposed to be stable with no more than 20 scans.



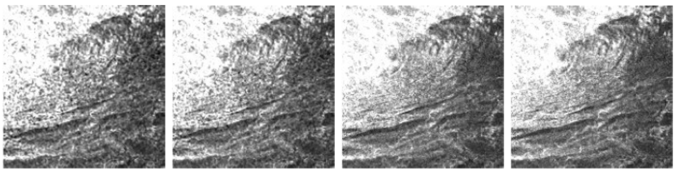
(a) MRE of shape parameter (b) MRE of scale parameter

Fig.3 MREs of parameters versus scan number

The pixel maps of the spatially-varying shape and scale parameters with different scan number t=1, 3, 20, and 35, respectively, are shown in *Fig.4*, in order to observe the variation tendency of full-scene parameter estimation. It shows that the pixel maps for both parameters are blurry at the beginning of estimation with t=1, and performances improve obviously with the increase of the scan number to t=3. Moreover, the pixel maps become much clear and almost invariable when the scan number t is 20 and 35. Comparing the pixel maps with t=1 to the ones with t=35, it is obvious that the MSRB-BiP estimator can provide much better estimating performance of parameters in the SV-GP clutter model than the traditional BiP estimator due to the recursive processing among multiple scans.



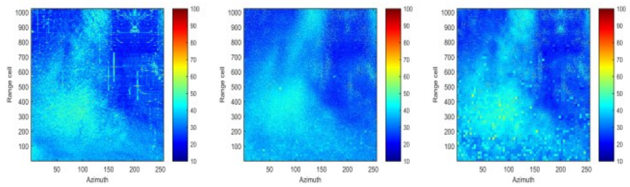
(a) Variation of shape parameter estimation via scans



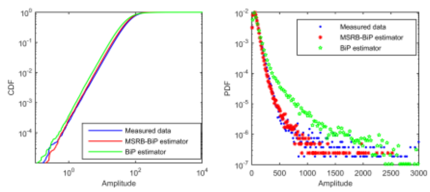
(b) Variation of scale parameter estimation via scans

Fig.4 Variation of parameter estimation by MSRB-BiP estimators

In order to demonstrate the robustness to outliers in data samples of the MSRB-BiP estimator, an extra experiment is supplemented here. Particularly, the MSRB method based on the ML estimator (MSRB-ML) is implemented here as a comparison object. Obviously, it will provide the most accurate estimation results for the SV-GP clutter model in the case without outliers, but it does not possess the outlier-robustness in the case with outliers. To generate outliers existed in the simulated scene, 0.5% range cells are chosen randomly from the total 2048×1280 cells and their amplitude follows the uniform distribution of the interval [10dB, 15dB] higher than the original mean amplitude of the clutter pluses. In the case with the scan number t=35 and the forgetting factor ξ=0.1, the MREs of both shape and scale parameters by the MSRB-BiP estimator are 0.2777 and 0.5320, respectively. Meanwhile, the MREs of parameters by the MSRB-ML estimator are 0.4270 and 1.3784, which are much higher than the MSRB-BiP estimator. It can be proved that the MSRB-BiP estimator is able to provide stable estimation even in the case with outliers, while the MSRB-ML estimator loses its high precision and gives poor estimation results.



(a) Measured data (b) MSRB-BiP estimator (c) BiP estimator



(d)Fitted CDF (e)Fitted PDF

Fig.5 Estimation performances on measured data

To demonstrate the practicability and effectiveness of the MSRB-BiP estimator in the large-scene detection of marine radar, a set of measured data of X-band bank-based radar is applied here for the performance test. Its sample size is 1024×256×5×18, which refers to the numbers of the range cells, the azimuth, the pulses and the scans, respectively, and the amplitude map in the 18^{th} scan is shown in *Fig.5*(a). In *Fig.5*, the estimation performances of the MSRB-BiP estimator and the BiP estimator in the 18^{th} scan are compared detailedly. Here, the small window size is tested to be regulated as 16×4 and the big one is 32×8, correspondingly. Besides, the forgetting factor for the MSRB-BiP estimator is fixed as 0.1 because the variation of measured scene is not very fast. To establish the visualized contrast, the amplitude maps of the SV-GP clutter model, which are simulated by the parameters estimated via the MSRB-BiP estimator and the BiP estimator, are shown in *Fig.5*(b) and *Fig.5*(c), respectively. It is clear that the amplitude map simulated by the MSRB-BiP estimator catches main varying characteristics of measured data in *Fig.5*(a) and remove outliers existed in the measured data slightly. On the contrary, the amplitude map simulated by the traditional BiP estimator is much noisy and suffers from the blocking artifact obviously. Besides, the fitted CDF and PDF are drawn in *Fig.5*(d) and *Fig.5*(e), respectively. It can be seen that the curves generated by the MSRB-BiP estimator show better fitness than the BiP estimator, especially the amplitude tail of the fitted PDF in *Fig.5*(e). Due to the analysis in *Fig.5*, the MSRB-BiP estimator can provide much better estimation performance and is able to describe clutter characteristics effectively.

V. CONCLUSION

It is important in performance optimization of radar target detection in sea clutter to describe clutter characteristic and develop effective parameter estimators. In this study, the spatially-varying compound-Gaussian model is proposed to fit varying characteristic of clutter in large scene. Besides, the MRSB estimator is provided to realize dynamic parameter estimation of spatially-varying clutter. The MRSB-BiP estimator, introduced as one of its application, exhibits much better estimate performance than BiP estimator in slowly-varying clutter scene. Furthermore, more applications of MRSB estimators are supposed to be studied later based upon existing estimators of traditional compound-Gaussian clutter models.

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