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Spatial-variant contrast maximization autofocus algorithm for ISAR imaging of maneuvering targets

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Dear editor,
High-resolution inverse synthetic aperture radar (ISAR) imaging is hypersensitive to range and azimuth spatial-variant phase errors [1, 2], which are usually caused by target's maneuvering motion. Some strategies have been proposed to solve the phase errors problem. Methods based on dominant scatterers phase tracking, such as multiple dominant scatterers synthesis method (MDSS) [3], can obtain well-focused imaging results if there exist dominant scattering centers in practical application. In view of the interference of noise on the dominant scatterers extraction, methods based on an evaluation index of the whole image were proposed, such as the maximum contrast phase autofocus algorithm [4]. However, for these traditional autofocus algorithms above, the phase error model is under the assumption that the phase errors are a function of fast and slow time [5], losing sight of the spatial-variant property of maneuvering targets.

In this study, a novel spatial-variant contrast maximization autofocus algorithm is proposed, where a parametric two-dimensional spatial-variant phase errors polynomial model is established. In the newfangled model proposed, the spatial-variant property can be compactly expressed by polynomial coefficient vectors, and the change of image projection plane (IPP) caused by maneuvering motion is also taken into account. Moreover, the polynomial coefficient vectors can be achieved by the maximum contrast optimization which is implemented by Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm [6]. Additionally, a method for adaptive polynomial order selection is also put forward. Real data experiments are provided for a clear demonstration of the proposed algorithm.

Signal model. For a maneuvering target, during the coherent processing interval (CPI), both the magnitude and direction of effective rotational vector (ERV) may be time variant, which is the cause of spatial-variant phase errors generated. As for direction, it is reasonable to assume that ERV rotates slowly with an uniform velocity in a certain plane due to short CPI. Since ERV is perpendicular to IPP, it is obvious that IPP rotates uniformly around radar line of sight (RLOS) too. In addition, as for magnitude, the rotational motion can be modelled by a L-order polynomial. Based on this, the two-dimensional spatial-variant phase errors model can be established by an L-order polynomial

$$\Phi(k,n,m) = \sum_{l=2}^{L} \left[(\alpha_l \cdot n + \beta_l \cdot m - \gamma_l) \cdot k^l \right] - \sum_{l=1}^{L} \varepsilon_l \cdot m \cdot k^{l+2}, \tag{1}$$

where α_l, β_l and γ_l represent the polynomial coefficients of the lth-order term of the range spatial-variant phase error, the azimuth spatial-

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variant phase error and the residual phase error, respectively; ε_l is the polynomial coefficients of the lth-order term of the phase error caused by rotation of IPP; n represents range bin, $n = [-N/2, -N/2+1, \ldots, N/2-1]^{\mathrm{T}}$, and N is the total number of range bins; k represents discretized slow time, $k = [0, 1, \ldots, M-1]^{\mathrm{T}}$, and M is the total number of azimuth bins; m represents azimuth bin, $m = [-M/2, -M/2+1, \ldots, M/2-1]^{\mathrm{T}}$; $L \geqslant 2$. For simplicity and clarity, we denote polynomial coefficient vectors $\boldsymbol{\alpha} = [\alpha_2, \ldots, \alpha_L]$, $\boldsymbol{\beta} = [\beta_2, \ldots, \beta_L]$, $\boldsymbol{\gamma} = [\gamma_2, \ldots, \gamma_L]$ and $\boldsymbol{\varepsilon} = [\varepsilon_1, \ldots, \varepsilon_L]$.

Spatial-variant contrast maximization autofocus algorithm description. Estimating the optimal polynomial coefficient vectors can be regarded as solving an unconstrained optimization problem in which polynomial coefficient vectors $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$ and $\boldsymbol{\varepsilon}$ are the variables of objective function. Generally, both image contrast and image entropy can be used as objective function, and they can achieve the same results. In this study, the former is chosen. The optimal polynomial coefficient vectors can be obtained by maximizing the objective function as follows:

$$\left\langle \tilde{\boldsymbol{\alpha}}, \tilde{\boldsymbol{\beta}}, \tilde{\boldsymbol{\gamma}}, \tilde{\boldsymbol{\varepsilon}} \right\rangle = \arg \max_{\boldsymbol{\alpha},\boldsymbol{\beta},\boldsymbol{\gamma},\boldsymbol{\varepsilon}} \{C\}, \tag{2}$$

where $C = \frac{\sigma}{\mu}$ is defined as the image contrast; σ and μ represent the mean and standard deviation of $|f_n(m)|$ respectively; $\tilde{u}_n(k)$ represents the total received signal and $f_n(m)$ is ISAR image obtained by applying azimuth fast Fourier transform (FFT) to $\tilde{u}_n(k)$; $\tilde{\boldsymbol{\alpha}}$, $\tilde{\boldsymbol{\beta}}$, $\tilde{\boldsymbol{\gamma}}$ and $\tilde{\boldsymbol{\varepsilon}}$ represent the optimal estimated results.

Herein, we use BFGS algorithm, an effective quasi-Newton method, to solve the unconstrained optimization problem as (2). What needs to be pointed out that, the process of the compensation and estimation for $\boldsymbol{\varepsilon}$ is almost the same as $\boldsymbol{\beta}$, so we do not make a separate deduction and explanation for it here. Let $\tilde{\boldsymbol{Q}}^{[l]} = [\tilde{\alpha}_l, \tilde{\beta}_l, \tilde{\gamma}_l]$ denote the polynomial coefficient vector of the lth-order term of the phase error model. Thus, the update formula of BFGS can be expressed as

$$\Delta\tilde{\boldsymbol{Q}}^{[u,l]} = \lambda^{[u,l]} \cdot \left(\boldsymbol{B}^{[u,l]}\right)^{-1} \cdot \nabla C\left(\tilde{\boldsymbol{Q}}^{[u,l]}\right), \tag{3}$$

where $\Delta\tilde{\boldsymbol{Q}}^{[u,l]} = \tilde{\boldsymbol{Q}}^{[u+1,l]} - \tilde{\boldsymbol{Q}}^{[u,l]}$ and the superscript u is the iteration number, $u = 1, \ldots, U$. $\lambda^{[u,l]}$ is the search step , which can be determined by Armijo criterion [7]. Armijo criterion, an inexact one-dimensional search, aims at preventing the objective function from falling into the local optimization. Moreover, $\nabla C(\tilde{\boldsymbol{Q}}^{[l]}) = (\frac{\partial C}{\partial \tilde{\alpha}_l}, \frac{\partial C}{\partial \tilde{\beta}_l}, \frac{\partial C}{\partial \tilde{\gamma}_l})$ is the gradient of objective function, which can be obtained as follows:

$$\begin{cases} \dfrac{\partial C}{\partial \tilde{\alpha}_l} = D \cdot \mathrm{Re}\left[\displaystyle\sum_{n=-N/2}^{N/2-1} \sum_{m=-M/2}^{M/2-1} (\mathrm{j} \cdot n \cdot F)\right], \\ \dfrac{\partial C}{\partial \tilde{\beta}_l} = D \cdot \mathrm{Re}\left[\displaystyle\sum_{n=-N/2}^{N/2-1} \sum_{m=-M/2}^{M/2-1} (\mathrm{j} \cdot m \cdot F)\right], \\ \dfrac{\partial C}{\partial \tilde{\gamma}_l} = D \cdot \mathrm{Re}\left[\displaystyle\sum_{n=-N/2}^{N/2-1} \sum_{m=-M/2}^{M/2-1} (\mathrm{j} \cdot F)\right], \end{cases} \tag{4}$$

where $D = \frac{1}{MN} \cdot [-(\frac{2}{\sigma} + \frac{\sigma}{\mu^2})]$, $F = \frac{f_n(m)}{|f_n(m)|} \cdot [\sum_{k=0}^{M-1} k^l \cdot \tilde{u}_n^*(k) \cdot \omega^{mk}]$ and $\omega = \exp(\mathrm{j}2\pi/M)$; $\tilde{u}_n^*(k)$ represents the conjugate of $\tilde{u}_n(k)$. $\boldsymbol{B}^{[u,l]}$ is the approximate matrix of Hessian matrix, which can be determined by

$$\boldsymbol{B}^{[u,l]} = \begin{cases} \boldsymbol{B}^{[u-1,l]}, & \left(\boldsymbol{y}^{[u,l]}\right)^{\mathrm{T}} \cdot \boldsymbol{s}^{[u,l]} \leqslant 0, \\ \boldsymbol{B}^{[u-1,l]} + \boldsymbol{Y}^{[u-1,l]} - \boldsymbol{S}^{[u-1,l]}, & \left(\boldsymbol{y}^{[u,l]}\right)^{\mathrm{T}} \cdot \boldsymbol{s}^{[u,l]} > 0, \end{cases} \tag{5}$$

where $\boldsymbol{Y}^{[u-1,l]} = \frac{\boldsymbol{y}^{[u,l]} \cdot (\boldsymbol{y}^{[u,l]})^{\mathrm{T}}}{(\boldsymbol{y}^{[u,l]})^{\mathrm{T}} \cdot \boldsymbol{s}^{[u,l]}}$ and $\boldsymbol{S}^{[u-1,l]} = \frac{\boldsymbol{B}^{[u-1,l]} \cdot \boldsymbol{s}^{[u,l]} \cdot (\boldsymbol{s}^{[u,l]})^{\mathrm{T}} \cdot \boldsymbol{B}^{[u-1,l]}}{(\boldsymbol{s}^{[u,l]})^{\mathrm{T}} \cdot \boldsymbol{B}^{[u-1,l]} \cdot \boldsymbol{s}^{[u,l]}}$; $\boldsymbol{s}^{[u,l]} = \tilde{\boldsymbol{Q}}^{[u,l]} - \tilde{\boldsymbol{Q}}^{[u-1,l]}$ and $\boldsymbol{y}^{[u,l]} = \nabla C(\tilde{\boldsymbol{Q}}^{[u,l]}) - \nabla C(\tilde{\boldsymbol{Q}}^{[u-1,l]})$.

It is obvious that BFGS algorithm only needs to calculate the gradient of objective function, which can be computed using N times M points FFT. Computing computational complexity by the number of complex multiplications, the computational complexity of M points FFT is $O(M \cdot \log_2 M)$. Thus, the total computational complexity of the proposed algorithm is approximately $O(N \cdot M \cdot \log_2 M)$. It needs to be pointed out that we usually have no additional knowledge of the maneuvering target's motion in reality so that an adaptive polynomial order selection method should be developed. The order of the polynomial phase error model can be determined adaptively when the estimated values of two consecutive image contrast are smaller than a pre-determined threshold. In general, 10^{-3} is usually chosen as the threshold in reality.

Experiments and analyses. The real data of a Yak-42 aircraft is used to verify the effectiveness of the proposed algorithm in this section. Herein, 10^{-3} is chosen as the threshold in adaptive polynomial order selection. From Figure 1(a) we can know, it is reasonable to use three-order polynomial to establish the spatial-variant phase error model. The ISAR images obtained by MDSS, phase adjustment by contrast

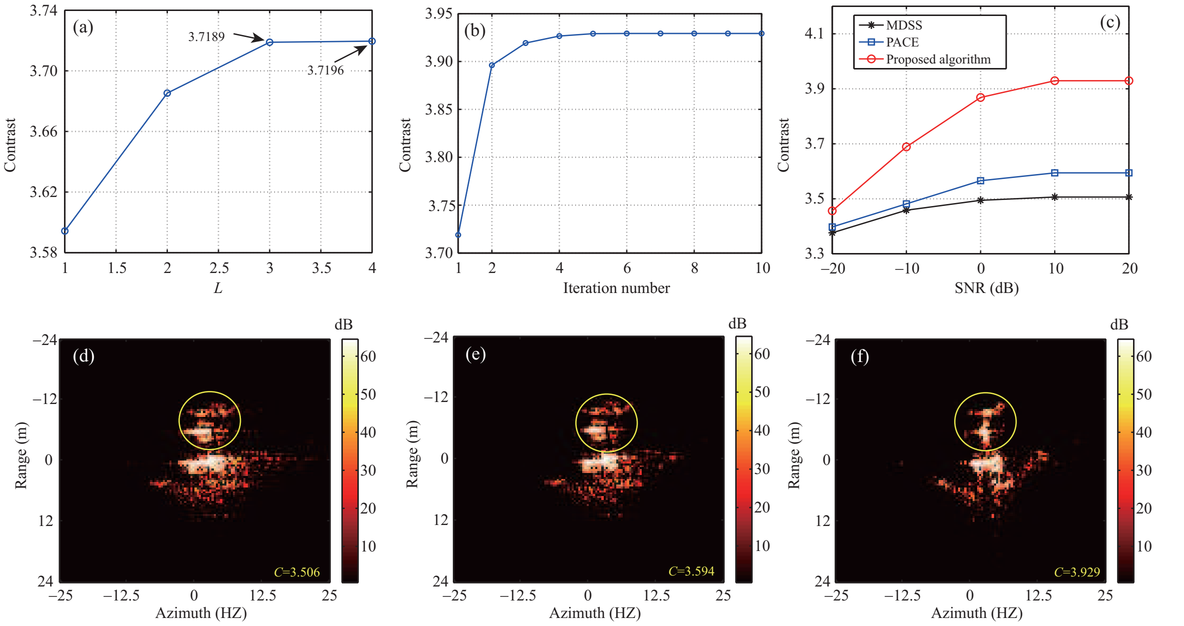

Figure 1 (Color online) Experimental results of real data. (a) Relationship between contrast and polynomial order; (b) relationship between contrast and iteration number; (c) relationship between contrast and SNR; (d) imaging result of MDSS method; (e) imaging result of PACE method; (f) imaging result of the proposed algorithm.

enhancement (PACE) [4] and the proposed algorithm are exhibited in Figures 1(d)–(f), respectively. Obviously, the ISAR images obtained by MDSS and PACE exist evident two-dimensional spatial-variant phase errors, which blur imaging results severely. However, the well-focused ISAR image can be generated by the proposed algorithm, which also can be seen from the image contrast marked in figures. Therefore, the effectiveness of the proposed algorithm can be illustrated. In addition, as shown in Figure 1(b), the proposed algorithm can generate well-focused ISAR image after around five iterations, which confirms the convergence and high efficiency of the proposed algorithm. One can note from Figure 1(c) that the experimental results obtained by the proposed algorithm under different signal-to-noise ratio (SNR) are much better than those of the other two autofocus algorithms, so the good robustness of the proposed algorithm to noise can be demonstrated.

Conclusion. In this study, a novel spatial-variant contrast maximization autofocus algorithm is proposed, in which a two-dimensional spatial-variant phase errors polynomial model is established. Implemented by BFGS algorithm, the maximum contrast optimization is utilized to achieve the polynomial coefficient vectors. Moreover, to select polynomial order adaptively, an adaptive polynomial order selection method is also introduced. Detailed experimental comparisons are given to confirm the effectiveness of the proposed algorithm.

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