Norm Optimization using Machine Learning Approach for Autofocus in mmWave SAR Imaging

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***Abstract*— Due to the shorter wavelength of mm-wave SAR for higher resolution, high-frequency phase error (HPE) can be generated even by small vibration of antenna phase center and distortion to SAR image becomes significant. For the problem, the machine learning approach can be utilized in SAR autofocus by classifying images and optimizing the objective function for autofocus. A hybrid form of L_1/ L_2-norm is adapted to the range compressed data corresponding to the input of the autofocus taking advantage of the convergence speed and the stability. Its convergence feature is analyzed and demonstrated in the simulation.**

***Keywords*— SAR, high-frequency phase error, autofocus, norm**

I. Introduction

A major challenge in high-resolution SAR system involves compensation for undesirable variations in the azimuth SAR phase history. The motion measurement errors varying many times over the azimuth aperture introduce high-frequency phase error (HPE) into the signal history which affects the side-lobe level, resulting in a loss of contrast in the SAR image. The HPE has more rapid variations over the coherent aperture. It is defined as the HF vibration in the condition of $|f \cdot T_a|>1$ where f is the vibrating frequency and T_a is the synthetic aperture duration [1]. The magnitude of HPE may be small compared to the wavelength corresponding to the radar center frequency. The subsystem budget is designed to suppress the influence of such HPE to a negligible level. However, as the operating frequency of SAR imaging with the mm-wave band, the influence of the platform vibration cannot be neglected when the vibrating amplitude is close to or even greater than the operating wavelength. It is common in airborne SAR platforms with flexible maneuverability whose movement includes translation and rotation. In conventional optimizing autofocus that utilizes the Shannon entropy or the L_p-norm optimization, there have been problems of iteration terminating prematurely or falling into local minima. The sensitivity to the metric value itself generates convergence problems or large powers of L_p-norm cause numerical problems in the optimization routines. An optimization problem to estimate the HPE and how L_1-norm affects the optimization process compared to L_2-norm will be discussed. The proposed hybrid regularizing form is characterized by providing different optimization paths along the direction of two-dimensional range compressed SAR data.

II. Background

The HPE includes the sinusoidal phase error (SPE) and wideband-random phase error (WRPE). The SPEs can be caused by trembling of the APC caused by vibration. For small ϕ_o, $J_o \simeq 1$, $J_1(\phi_o) = -J_{-1}(\phi_o) \simeq \phi_o / 2$, the Bessel approximation of the 1st kind is described as

$$e^{j\phi_o \sin(2\pi f_e t)} = \sum_{n=-\infty}^{\infty} J_n(\phi_o) e^{j2\pi n f_e t} \simeq 1 + \frac{\phi_o}{2}\left(e^{j2\pi f_e t} - e^{-j2\pi f_e t}\right) \quad (1)$$

which introduces paired echoes, two additional responses of amplitude $\phi_o/2$ at f_o-f_e and f_o+f_e. The peak side-lobes may be interpreted as spurious targets in a real SAR image. The resultant peak side-lobe ratio (PSLR) is

$$PSLR = \frac{\phi_o^{\ 2}}{4} = 4\pi^2 \left(\frac{a_s}{\lambda_c}\right)^2 \quad (2)$$

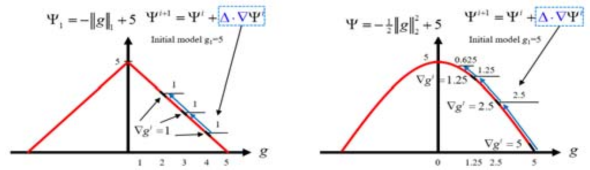
On the other hand, the WRPE is caused by unwanted random movements between the APC and the target that spreads out energy widely across the impulse response and contribute to increase the integrated side-lobe ratio (ISLR) which results in contrast degradation. Let σ_ϕ is a RMS value of the WRPE. The relationship between the ISLR and the WRPE is described as

$$ISLR \simeq e^{\sigma_\phi^2} - 1 \simeq \sigma_\phi^2 = \left(\frac{4\pi\sigma_r}{\lambda_c}\right)^2 \quad (3)$$

where σ_r is a standard deviation of the uncompensated APC motion. The acceptable HPE is related to the system budget of PSLR and ISLR imposed on the autofocus. For a given requirement, the allowable uncompensated sinusoidal and random motion error varies inversely proportional to the λ_c^2.

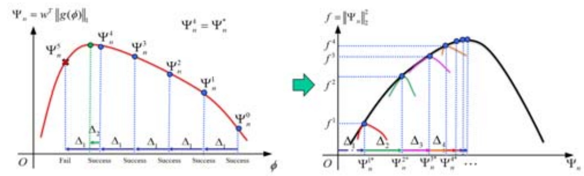
III. Proposed Method

Consider a maximization problem with the initial value Ψ^1=0 and the step size Δ=0.5 in Fig.1. The L_1-norm in Fig.1(a) makes ten iterations of $\Psi^{i+1}= \Psi^i+0.5\times1$ until reaching the maximum. On the other hand, with L_2-norm in (b) where the step size Δ=0.5, the gradient is Ψ^i causing every step to be halfway towards the maximum with the iterations of $\Psi^{i+1}=\Psi^i+0.5\Psi^i$. Therefore, the metric never reaches the maximum regardless of how many steps are taken. Though the L_2-norm can make the metric reach the maximum in a single step if Δ is so large, it may still make Ψ reach the maximum when used together with an objective function that tries to minimize the error w.r.t. Ψ. Therefore, the



(a) (b)

Fig. 1. Maximization Example with (a) L1-norm, (b) L2-norm.



(a) (b)

Fig. 1. Hybrid Maximization. (a) L_1-Norm range Max. with Constant Step Size. (b) L_2-Norm azimuth Maxi. with Variable Step Size.

gradient of the L_2-norm is more sensitive to its value compared to the L_1-norm that is relatively stable but not robust. For finding and removing the closest estimation of the HPE in SAR history, it is required to perform the iterative process related to a cross-correlation. After optimizing the n-th range objective function f_n for single range bin, it can be expanded to a multi-range bin problem by superposition as $f=f_0+\ldots+f_{N-1}$. The local objective function f_n for a single range is a nonlinear function of a range characteristic value Ψ_n described as

$$f_n = \left(\Psi_n(g)\right)^2 \text{ with } p>1 \tag{4}$$

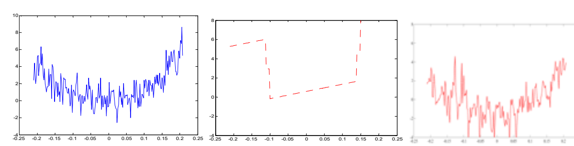
The squared nonlinear form gives weight to a range-bin depending on its SNR. It makes an effect to gives more weight to the range bin with high SNR. A L_1-norm is more robust and suitable for calculating the change of range compressed data in a one-dimensional vector space and including the selection of range bin to be cross-correlated described as

$$\Psi_n = \sum_{k=1}^{M} w_k \left|g[n,k]\right| \tag{5}$$

which is the weighted L_1-norm where w is the weighting vector determined depending on the scene characteristic. If there is a range bin involving dominant scatterers, the weighting component $w_k=|g[n^*,k]|$ may be useful for a quick convergence where n^* is the index of the range bin with the maximum power. In this case, the PE is estimated along the direction of increasing the inner product between each range bin and the range bin with the highest SNR. If the background clutter is homogeneous such as sea or forest, the weighting with the uniform distribution can be useful. The unified objective function of the (4) and (5) is the hybrid form of the L_1-norm defined along the azimuth direction and the squared L_2-norm defined along the range direction. This reflects that the rows and columns of the RC data are defined in the different domains. Because the autofocus process takes place between range compression and azimuth compression, the raw signal is range compressed data. The reason for using different norms in the range and azimuth directions is that the scale of the raw RC data in each direction is quite different. The evaluation of metric deals with small values along the azimuth direction and combined large values along the range direction. The hybrid of different norms can take both advantages adaptively for the scale of the raw data value. The L_2-norm is stable but sensitive to the input value and the convergence is slow. On the other hand, L_1-norm is not sensitive to the input and robust as a result but less stable. Fig. 1 describes the iterative searching procedure. The L_1-norm maximization with constant step size provides fast convergence speed w.r.t. the small values in the Fourier domain along the azimuth direction as shown in Fig. 1(a). The L_2-norm maximization with variable step size provides stability with high convergence accuracy w.r.t. the combined large values in the image domain along the range direction as shown in Fig. 1(b). The hybrid of L_1-L_2 norm enables to take both advantages adaptively for the scale of the azimuth Fourier domain value and range image-domain value, respectively.

IV. Simulation Results

Fig.3 compares the PE results by the minimum entropy (ME) before and after image scaling. In our experimental results, there was a problem that the ME sometimes fails to estimate a phase error. Fig.3(b) is an imprecise estimation for (a) because the convergence of the ME is very sensitive to the scale of the raw data values and its iteration is terminated quickly when a small value is encountered. This problem was initially addressed by scaling the objective function and the gradients by a constant. or scale the complex image in an acceptable range. This prevented the sums of very large or very small numbers from occurring. Fig.3(c) shows a good estimate of the HPE in (a) by appropriately scaling the intensity of the image.



(a) (b) (c)

Fig.3. (a) Actual HPE. (b),(c) Estimation before and after Optimization, respectively.

V. Conclusions

The HPEs often occur in maneuverable airborne SAR causing spurious targets and contrast degradation in SAR imagery.

In contrast with the conventional metric-optimization approach the proposed metric reflecting the focus level of a SAR image is adapted to the range compressed data corresponding to the input of the autofocus process, taking advantage of the convergence speed and the stability in its optimization by adopting the hybrid form of L_1 and L_p-norm. We conduct research to find optimal metric based on contents of image applying the machine learning approach. In the simulation part, the performance is demonstrated for the HPE with image entropy as a cost function

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