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Quantitative Assessment of CFRP-concrete Cylinders Using Synthetic Aperture Radar Images

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Abstract

A feature extraction algorithm is proposed to quantitatively assess the condition of intact and damaged CFRP (carbon fiber reinforced polymer)-wrapped concrete cylinders using synthetic aperture radar (SAR) images. The proposed algorithm converts SAR images into a simplified representation, based on the shape, size, and amplitude of SAR images. In this approach, the shape of scatterers in a SAR image is characterized by average Gaussian curvature (K), area ratio (R), and SAR amplitude (I) and represented by a K - R - I curve. SAR images of intact and damaged CFRP-wrapped concrete cylinders were generated by a stripmap SAR imaging radar system (10.5 GHz) at various inspection angles (0° , 15° , 25° , 30° , 45° , and 60°). From our experimental result, it is found that the K - R - I representation of SAR images is capable of distinguishing damaged SAR images from intact ones at different inspection angles. Quantitative dissimilarity between the K - R - I curves of intact and damaged specimens is assessed by coefficient of correlation and compared with the signal-to-noise ratio (SNR) of SAR images. It is found that the dissimilarity of K - R - I curves is closely related to the SNR of SAR images, demonstrating the feasibility and potential of the proposed K - R - I representation.

Keywords: Radar NDE, synthetic aperture radar, damage detection, CFRP-concrete

INTRODUCTION

In the remote sensing of concrete structures for condition assessment, radar and microwave sensors are powerful tools to inspect surface and subsurface damages, among other sensors such as LiDAR and thermal infrared. When using radar and microwave sensors, synthetic aperture radar (SAR) imaging algorithms can be used to improve the resolution of radar images for better detection, characterization, and diagnosis. Integrated radar signals rendered in the SAR image domain can be used for target detection (e.g., range, size, damage), change detection [1], feature extraction [2, 3], as well as damage detection [4, 5]. Most remote sensing applications used cross-range—cross-range SAR images for surface inspection, while some applications used range—cross-range SAR images for subsurface inspection [6,7]. In civil engineering, SAR imaging has also been applied in the subsurface damage (debonding) detection of fiber-reinforced polymer (FRP) wrapped/strengthened concrete structures to assess the quality of FRP repair/strengthening construction [6]. The capability of radar signals on penetrating through dielectrics (e.g., FRP, concrete) enables imaging radar to detect subsurface defects or to evaluate the aging of materials. As a result, studying the features of integrated scatterers in SAR images is key to the success of structural condition assessment using SAR imaging.

In general, subsurface damage detectability of reflected and scattered radar signals depend on the geometry (e.g., shape, surface roughness) and electromagnetic composition (e.g., property, distribution, contrast) of the target, radar frequency (wavelength), inspection range, incident angle, and inspection scheme (monostatic or bistatic). After integrating radar signals into SAR images, the scatterers in a SAR image represent the combined effect of all above-mentioned

factors. Consequently, scatterers are used for condition assessment since they represent the presence of either a dielectric interface or change of geometry. Comparing two SAR images of intact and damaged structures facilitates damage detection and localization in such approach.

However, difficulties arise when performing direct comparison of SAR images. Direct comparison is usually carried out by background subtraction in order to remove background noise and to increase signal-to-noise ratio (SNR). In such scheme, an intact structure represents the background signal and a damaged structure represents both background and target signals. In order to correctly remove the background signal in a range—cross-range SAR image, perfect spatial alignment (both translation and rotation) of two images is required but very difficult to achieve in the field. Meanwhile, direct comparison of SAR images also utilizes only the amplitude information, which could be misleading for interpretation. This is because two SAR scatterers caused by intact and damaged structures may result in identical maximum amplitude but different shapes (distribution of amplitudes). As a result, quantitative analysis of SAR images for structural condition assessment requires delicate arrangement and is experience-oriented.

In view of the difficulties in the use of SAR imaging for structural condition assessment, the objective of this paper is to present a simplified representation to quantify SAR images for damage detection. In this simplified representation, comparison of (range vs. cross-range) SAR images (matrices) is converted into the comparison of simplified K-R-I curves (vectors) generated from SAR images. Global measures including shape (K or Gaussian curvature), contour area ratio (R) and SAR amplitude (I) of each SAR image are computed for quantitative comparison.

In what follows, theoretical basis of the proposed, simplified representation is first provided. Application of the simplified representation is made on a CFRP-concrete cylinder that is inspected by a laboratory stripmap SAR imaging system. Finally, research findings are discussed and concluded.

THEORETICAL BACKGROUND

1. Synthetic Aperture Radar Imaging

In synthetic aperture radar imaging, two formats are usually used for different applications; cross-range—cross-range (r_x - r_x) and range—cross-range (r - r_x). Fig. 1 illustrates these two formats, using a cylinder as example. In Fig. 1, the representation of a cylinder in r_x - r_x images is a rectangle, while the one in r - r_x images is a circle. In this research, subsurface sensing is achieved by using range—cross-range (r - r_x) SAR images. Formation of range—cross-range (r - r_x) SAR images are briefly explained in this section.

Range—cross-range (r - r_x) SAR images are generated by backprojection algorithms (Kak and Slaney 1999). Consider a stripmap SAR imaging mode shown in Fig. 2. At each radar location, an incident wave with unit amplitude is defined by

(Kong 2000) (Fig. 3)

$$\psi_{inc}(\vec{r}) = \frac{1}{r} \cdot \exp(i\vec{k}_i \cdot \vec{r}) \quad (1)$$

where $\bar{k}_i = k_{ix} \hat{x} - k_{iy} \hat{y}$ is the incident wave vector and \bar{r} is the relative position vector from the radar to any observation point, $|\bar{r}| = r$. The scattered field from scatterer j at \bar{r}_j and observed at \bar{r} is (Tsang et al. 2000)

$$\psi_{scat}(\bar{r}, \bar{r}_j) = \frac{s_j(\bar{r}, \hat{k}_i)}{|\bar{r} - \bar{r}_j|} \exp(ik|\bar{r} - \bar{r}_j|) \cdot \psi_{inc}(\bar{r}) \quad (2)$$

where $s_j = s_j(\bar{r}, \hat{k}_i)$ is the scattered amplitude at scatterer j due to an incident wave at \hat{k}_i , observed at \bar{r} . By neglecting the interaction among scatterers, the total scattered field from N scatterers observed at \bar{r} is the summation of the scattered fields from all scatterers. Eq.(3) is actually a sliced projection of the two-dimensional (2D) Fourier transform (FT) of the domain Ω_s .

$$\psi_{scat}(\bar{r}) = \sum_{j=1}^N \frac{s_j(\bar{r}, \hat{k}_i)}{|\bar{r} - \bar{r}_j|} \cdot \exp(ik|\bar{r} - \bar{r}_j|) \cdot \psi_{inc}(\bar{r}) \quad (3)$$

where $\bar{k}_s = k_{sx} \hat{x} + k_{sy} \hat{y}$ is the scattering direction vector. $\bar{k}_s = -\bar{k}_i$ when the radar operates in monostatic mode. Without losing generality, consider the case of single scatterer here. Knowing that $k = \omega/c$ and $\theta = \theta_i = \tan^{-1}(k_{iy}/k_{ix})$, Eq. (2) can be written by

$$\psi_{scat}(\omega, \theta) = \psi_{scat}(k, \bar{r}_s) = \frac{s_\theta}{r^2} \cdot \exp\left[i \frac{r}{c} \omega (1 + \cos^2 \theta - \sin^2 \theta)\right] \quad (4)$$

In backprojection algorithms, one-dimensional (1D) inverse FT (IFT, line projection) is first performed to generate sub-images. The final image is rendered by summing up all sub-images. The center in backprojection images is coincided with the center of the scatterer by performing a modulation operation in frequency domain or a convolution operation in time domain. The shifting-back step in the backprojection algorithm in frequency domain is performed by applying a ramp filter in which frequency ω_n is shifted back by a carrier frequency ω_c (Desai and Jenkins 1992). Scattering response in sub-images can be described by

$$P(v, \theta) = \int_{\omega_{\min}}^{\omega_{\max}} d\omega \cdot \psi_{\text{scat}}(\omega - \omega_c, \theta) |\omega - \omega_c| \cdot \exp(-i\omega v) \quad (5)$$

$$= \frac{s_\theta}{r^2} \cdot \int_{\omega_{\min}}^{\omega_{\max}} d\omega \cdot |\omega - \omega_c| \cdot \exp \left[i \frac{r}{c} (\omega - \omega_c) (1 + \cos^2 \theta - \sin^2 \theta) - i\omega v \right] \quad (6)$$

where v is the spatial variable of the 1D IFT projection. Translating the local 1D IFT coordinate $(v, P(v, \theta_s))$ to the global polar coordinate (r, ϕ) indicates that

$$v = r \cos(\phi - \theta_s) \quad (7)$$

Transforming from $P(v, \theta)$ to $P(r \cos(\phi - \theta), \theta)$ is usually associated with upsampling in order to improve image quality. In other words, $P(r \cos(\phi - \theta), \theta)$ is the interpolated version of $P(v, \theta)$. The final backprojection (range—cross-range) image is obtained by integrating the sub-images along the entire synthetic aperture.

$$I(r, \phi) = \int_{-\theta_{\text{in}}/2}^{\theta_{\text{in}}/2} d\theta \cdot P(r \cos(\phi - \theta), \theta) \quad (8)$$

This process can be conceptually illustrated by Fig. 5. Eq. (8) can be converted into its Cartesian form by

$$x = r \cos \phi \quad (9)$$

$$y = r \sin \phi \quad (10)$$

such that range—cross-range images can be obtained as long as the orientation of synthetic aperture is specified. Computational issues related to image interpolation can be found in the texts on SAR (Carrara et al.1995; Soumekh 1999). Major advantages of backprojection algorithms include: (1) lower and localized artifact levels than frequency-domain algorithms, (2) easy adjustment to an approximate inverse formula for perturbed problems, (3) readily for parallel computing with limited interprocessor communications, and (4) simple motion compensation by time-shift operation (McCorkle and Rofheart 1996; Nilsson and Anderson 1998).

2.Simplified Representation of Radar Images

In this paper, a simplified representation is proposed to convert range—cross-range SAR images ($I(r, r_x)$) into three-dimensional (3D) curves for quantitative analysis. This conversion is performed by calculating the following properties of SAR images.

$$K_{avg}(I_i) = \frac{1}{n} \sum_{i=1}^n K_i(x, y) = \frac{1}{n} \sum_{i=1}^n \left[\frac{\frac{\partial^2 I_i}{\partial x^2} \frac{\partial^2 I_i}{\partial y^2} - \left(\frac{\partial^2 I_i}{\partial x \partial y} \right)^2}{1 + \left(\frac{\partial I_i}{\partial x} \right)^2 + \left(\frac{\partial I_i}{\partial y} \right)^2} \right] \quad (11)$$

$$R_A(I_i) = \frac{A(I_i)}{A_{max}} \quad (12)$$

where $K_{avg}(I_i)$ = average Gaussian curvature [8] at a given SAR amplitude I_i , $R_A(I_i)$ = area ratio at a given SAR amplitude I_i , A_{max} = maximum closed area of the scatterer. The reason for calculating these two parameters is mainly to quantify the scattering phenomenon of radar signals (electromagnetic waves) in SAR images. When a point target is imaged by SAR, its scattering pattern will be circular (or circular scatter). When a rectangular target is imaged by SAR, its scattering pattern will be irregular, containing specular returns and edge reflections. If dielectric targets are encountered, multiple reflections from inside the target can be expected, making the scattering pattern even more complicated to interpret. In this paper, average Gaussian curvature and area ratio, both at given SAR amplitudes, are calculated to quantify the change of scattering pattern in SAR images. Average Gaussian curvature is used to measure the distribution of SAR amplitudes in space, while area ratio is used to measure the electromagnetic property of the target. The proposed representation is described by a procedure shown in Fig. 5. After applying the procedure, original SAR images is converted into (K_{avg}, R_A, I_i) curves.

APPLICATIONS

1. Artificial Objects

To demonstrate the feasibility of the proposed simplified (or K-R-I) representation, two artificial, simple 3D objects are considered; a cylinder and a cone. Fig. 6 shows the 2D and 3D forms of an artificial, cylinder-type SAR image with its K-R-I curve. Fig. 7 shows another example using an artificial, cone-type SAR image.

In Fig. 6, constant R_A and constant K_{avg} suggest a uniform amplitude distribution, while varying R_A and constant K_{avg} suggest a non-uniform amplitude distribution with consistent pattern (shape).

2. Steel Plate

A rectangular steel plate (40cm-by-60cm-by-2cm) was used in generating real SAR images for testing the proposed representation algorithm. A laboratory 10.5GHz central frequency imaging radar system with 4GHz bandwidth was used to generate stripmap SAR images of the plate. Fig. 8 shows a photograph of the plate and its SAR image. The physical configuration of the plate in Fig. 8(b) corresponds to the SAR image plane (range—cross-range) in Fig. 8(c). A 3D representation of the image is provided in Fig. 8(d). The contour line at a given SAR amplitude ($I = 1,000$) for calculating K_{avg} and R_A is shown in Fig. 8(e) as an example. After calculating the (K_{avg} , R_A) for different SAR amplitudes (I_i), the K-R-I curve of the SAR image is obtained as shown in Fig. 8(f). In Fig. 8, it is shown that amplitude change is continuous and the distribution

of SAR amplitudes (shape of scatterer) is irregular in real SAR images. Note that the magnitude of K_{avg} values in this rectangular steel plate is in the range of [0, -0.02].

3. CFRP-concrete Cylinder

An artificially damaged CFRP-wrapped concrete cylinder was used to examine the performance of proposed representation algorithm. A concrete cylinder specimen with a height of 30cm and diameter of 15cm was fabricated and wrapped with a carbon fiber reinforced polymer (CFRP) layer. The FRP layer was adhered to the concrete cylinder by epoxy resin. A 5cm-by-5cm-by-0.5cm artificial defect (made of Styrofoam) was embedded at the interface between the concrete and the FRP layer and targeted for subsurface defect detection. This defect size was chosen to verify the feasibility of both radar imaging (10.5 GHz, wavelength = 2.86cm) and the proposed K-R-I representation. Different sizes of defect can be considered with the use of different radar frequencies. The water-to-cement ratio of concrete was 0.5, and the specimen was moist-cured for 28 days before the wrapping of an FRP layer. The side of the cylinder with a subsurface defect is the damaged side, whilst the side without the defect is the intact side of the cylinder. Design of the CFRP-concrete cylinder is illustrated in Fig. 9.

Stripmap SAR imaging measurements at $\theta = [0, 15, 25, 30, 45, 60]$ degrees were carried out, and their K-R-I curves were generated as shown in Figs. 10-21. The reason for conducting SAR imaging at different angles is due to the angular dependence of target signals representing the presence of subsurface defect, as reported in literature [9].

Comparing Figs. 10 and 11, it is found that specular return dominates the intact response (Fig. 10) since the front surface of the FRP-concrete cylinder is perpendicular to the line of sight of radar at $\theta = 0$ degree. Compared to the SAR response of a steel plate in Fig. 8, it is also found that the SAR amplitudes in Fig. 10 are not distributed uniformly along the cross-range direction. This is because the surface of FRP overlay is unsmooth and rugged. On the other hand, in Fig. 11, SAR amplitude of the damaged side of FRP-concrete cylinder contains both the specular return from the front surface and the scattering signal due to a subsurface defect. As a result, some SAR amplitudes are reduced and some are amplified. To account for the shape change (amplitude and its spatial distribution) in SAR images, the proposed representation was applied and two distinctive K-R-I curves were obtained. Same image processing was applied to SAR images of intact and damaged sides of the CFRP-concrete cylinder at $\theta = 15, 25, 30, 45, 60$ degrees, as shown in Figs. 12~21.

In Figs. 12-21, it is demonstrated that the SAR images of both intact and damaged sides of the CFRP-concrete specimen depend on inspection angle, in terms of SAR amplitude and the distribution SAR amplitude. Such change is also reflected in the K-R-I representation of each SAR image.

4. Validation of the proposed algorithm

To validate the performance of the proposed K-R-I representation on condition assessment of structures, a forward study was conducted by comparing the coefficient of correlation between K-R-I curves with the signal-to-noise ratio in the SAR images (SNR_I) of intact and damaged

sides of a CFRP-concrete cylinder. The hypothesis was that the K-R-I curve of intact cylinder has a low coefficient of correlation with the one of damaged cylinder, suggesting the difference between an intact side SAR image from an damaged side SAR image. SNR_I was computed by comparing the SAR amplitude at the location of a known defect with the SAR amplitude at the location without a defect. It is defined by

$$SNR_I = \frac{I_{dam}}{I_{int}} \quad (13)$$

where I_{dam} = SAR amplitude at the location with a known defect (damaged), I_{int} = SAR amplitude at the location without a defect (intact). Inspection angle was also considered in this validation since all SAR images (or K-R-I curves) are dependent on selected inspection angle. Fig. 22 describes the overview of this forward study.

SNR_I values defined by Eq. (13) were calculated in this forward study in which the location of a subsurface between intact and damaged SAR images are listed in Table 1, as well as the coefficients of correlation between intact and damaged K-R-I curves. These values are illustrated in Fig. 23. It is noteworthy to point out that, only two K-R-I curves of identical length can be compared when computing their coefficient of correlation.

In Fig. 23, it is found that the SNR_I curve and the coefficients of correlation of K – R – I curves show almost opposite trend. This is because, in the SNR_I approach, the higher the SNR_I value is, the R – I approach, the more dissimilarity (lower values of coefficient of correlation) between an intact K – R – I curve and an unknown K – R –

I curve, the more likely to indicate the presence of damage. In other words, in the K – R – I approach, the lowest value of coefficient of correlation (highest dissimilarity between an intact K – R – I curve and an unknown K – R – I curve) suggests the presence of defect at an optimal inspection angle. This is validated by the opposite trend of the coefficient of correlation curves in Fig. 23.

DISCUSSION

Local vs. global

When using SAR images for damage localization, perfect alignment is needed in order to perform accurate background subtraction. This requires identical experimental setup for intact and damaged structures, which can be difficult to achieve in the field. If the SNR_I approach is adopted, a priori knowledge about possible damage locations must be provided in order to perform accurate background subtraction. However, the proposed K-R-I representation does not need to know the location of a defect. Instead, it compares the shape and size distributions at various SAR amplitudes between intact and damaged structures. In other words, the proposed K-R-I representation is a global method.

Effect of inspection angle

In Figs. 8, 11, 14, 17, 20, and 23, shape and length of K-R-I curves vary in both intact and damaged sides of the FRP-concrete cylinder. This is due to the nature of stripmap SAR imaging using monostatic radar configuration. When the imaging radar captures the specular return of radar signals ($\theta = 0\text{-deg.}$), strong background is likely to cover the scattering response of a

defect (Figs. 6~8). When the monostatic imaging radar inspects a damaged structure at a steep angle ($\theta = 60\text{-deg.}$), both the background and the defect signals are weakened and, consequently, their K-R-I curves are changed. In other words, K-R-I curves will change with the variation of inspection angle.

Limitations

The proposed K-R-I representation has limitations when applied to real structures. First of all, it is a global approach and does not provide the location information of a defect. Although the K-R-I curves still preserve features of shape and size (relative) of SAR scatterers at different SAR amplitudes, generation of K-R-I curves from SAR images does not require the knowledge of coordinates (local or global). Therefore, K-R-I curves do not provide any spatial information for locating defects. Secondly, due to the use of relative area ratio, two SAR scatterers with identical shapes (amplitude distributions) but different sizes will lead to identical K-R-I curves. This is because that the concept of damage detectability in the proposed K-R-I approach is based on the coupled variation of shape and size at different SAR amplitudes. This limitation may be removed by using absolute areas instead of relative area ratios.

CONCLUSIONS

A simplified representation utilizing the shape (K_{avg}), size (R_A) and amplitude (I_i) of synthetic aperture radar (SAR) images is proposed to extract the features in SAR images and to overcome existing difficulties in quantitatively comparing SAR images for condition assessment. The

proposed K-R-I representation is a global assessment of SAR images, based on the concept of shape-size coupling at different SAR amplitudes. From the application on a CFRP-concrete cylinder, it is demonstrated that the proposed K-R-I representation can differentiate intact SAR images from damaged SAR images. The performance of the K-R-I approach is also validated by traditional signal-to-ratio (SNR) approach. While this approach is limited by its global feature and unable to differentiate two same-shape-but-different-size SAR images, further research can be conducted to improve these properties.

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Disclaimer:

The views, opinions, findings and conclusions reflected in this presentation are the responsibility of the authors only and do not represent the official policy or position of the USDOT/OST-R, or any State or other entity Reference.

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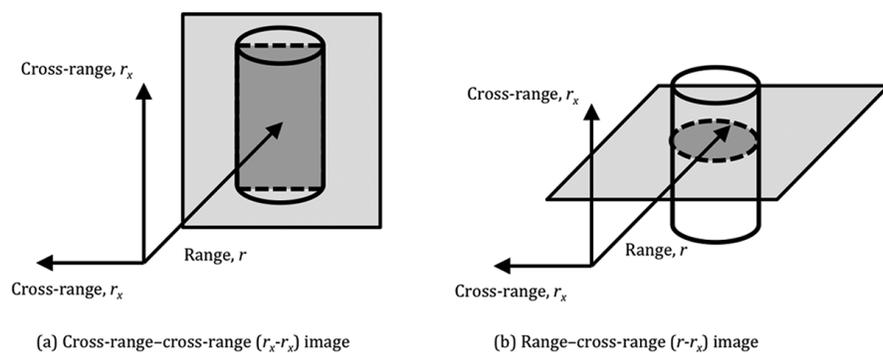
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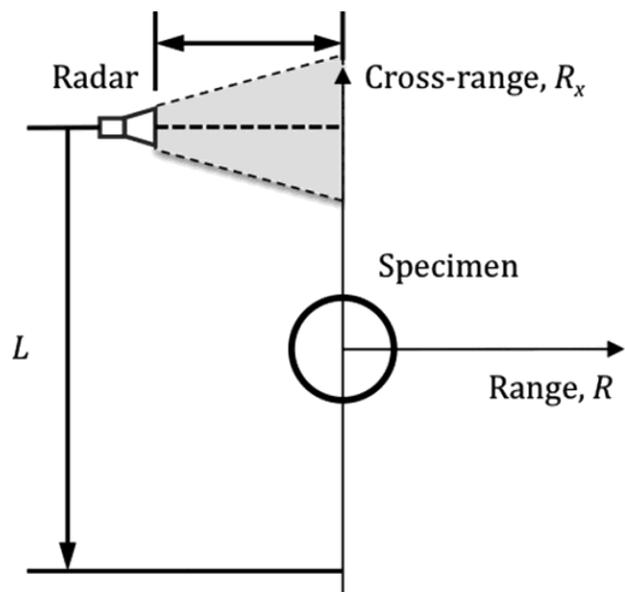
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Fig. 1. Two formats of SAR images



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Fig. 2. Stripmap SAR imaging mode



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Fig. 3. Scattering of N point scatterers

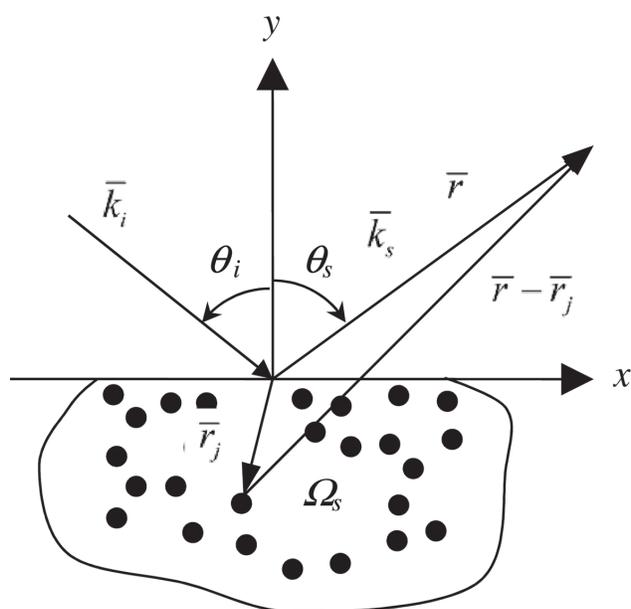
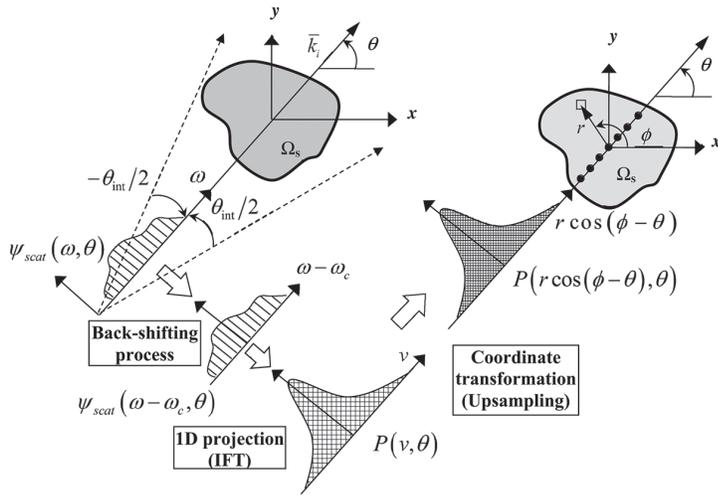
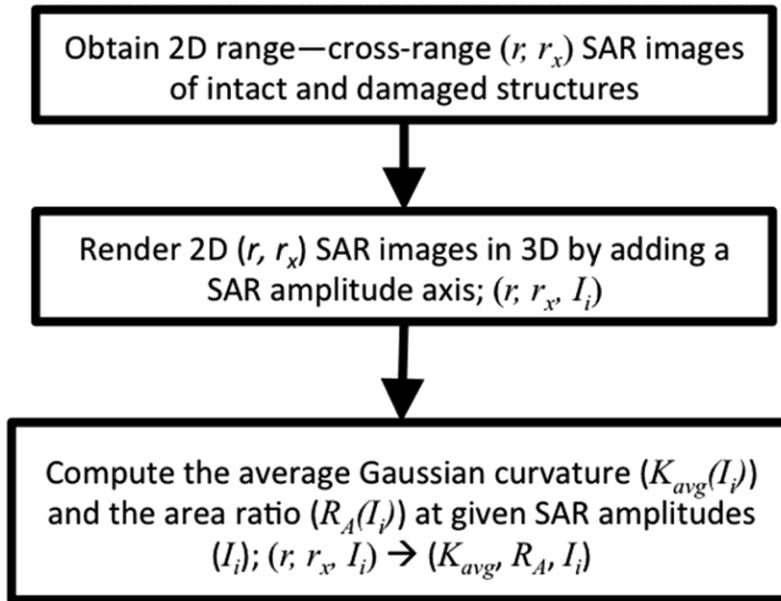


Fig. 4. Conceptual description of backprojection algorithms (Yu 2011)



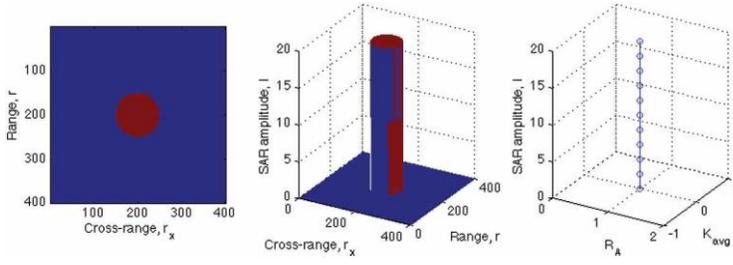
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Fig. 5. Procedure of the proposal simplified representation



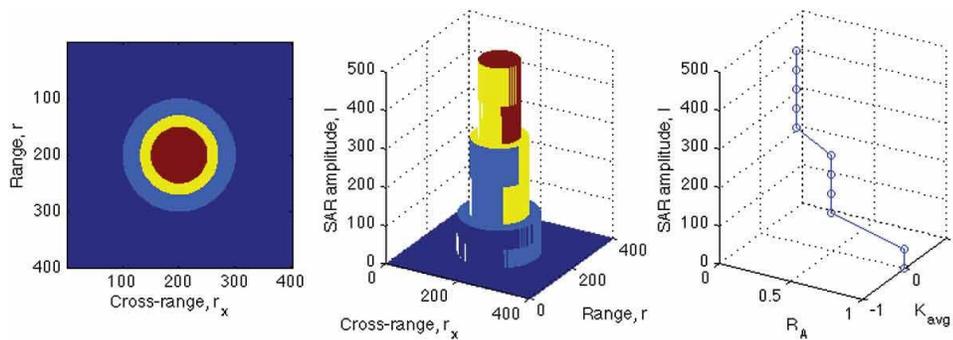
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Fig. 6. Application of the K-R-I representation using a cylinder as example



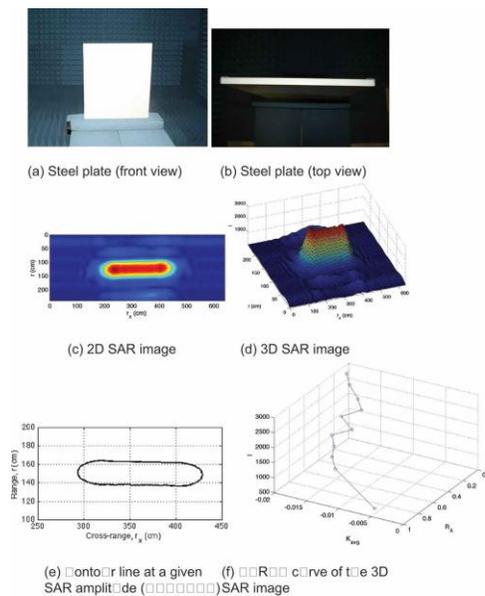
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Fig. 7. Application of the K-R-I representation using a cone as example



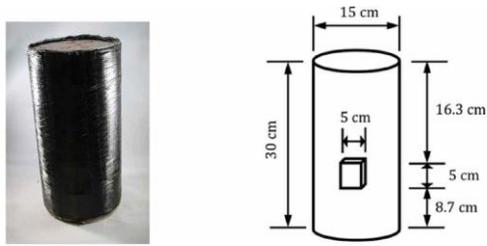
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Fig. 8. Rectangular steel plate, its SAR image and K-R-I curve

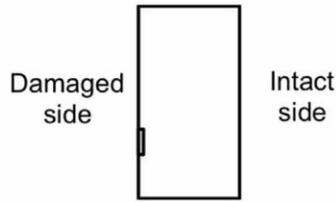


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Fig. 9. Design of an artificially damaged CFRP-concrete cylinder



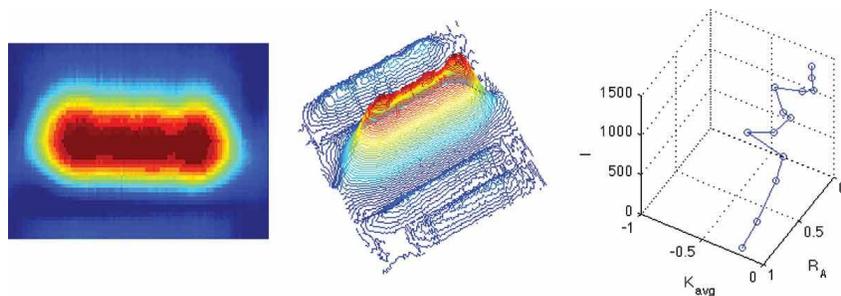
(a) CFRP-concrete cylinder (b) Design of the cylinder



(c) Damaged and intact sides

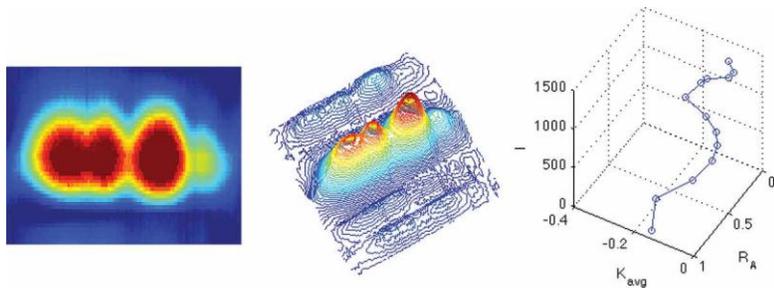
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Fig. 10. Stripmap SAR image and its K-R-I curve, intact side, $\theta = 0$ -deg.



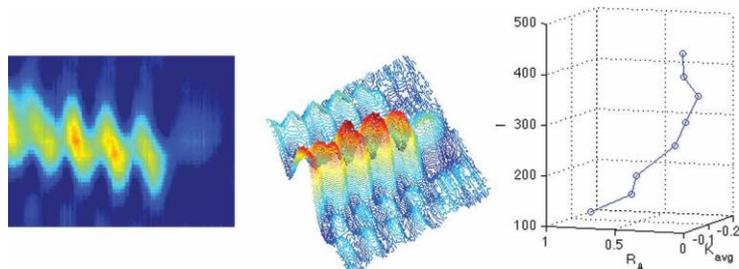
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Fig. 11. Stripmap SAR image and its K-R-I curve, damaged side, $\theta = 0$ -deg.



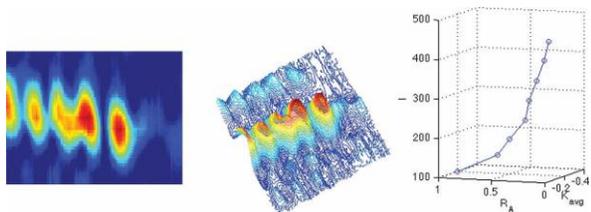
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Fig. 12. Stripmap SAR image and its K-R-I curve, intact side, $\theta = 15$ -deg.



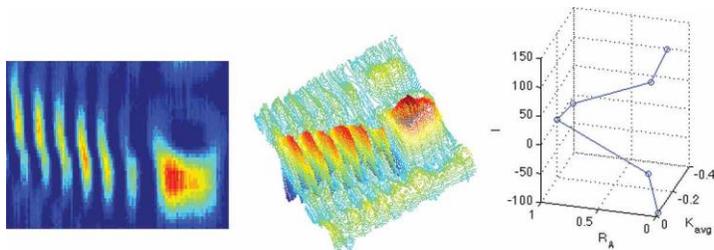
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Fig. 13. Stripmap SAR image and its K-R-I curve, damaged side, $\theta = 15$ -deg.



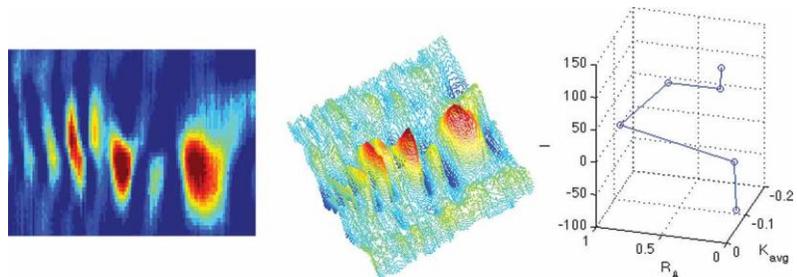
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Fig. 14. Stripmap SAR image and its K-R-I curve, intact side, $\theta = 25$ -deg.



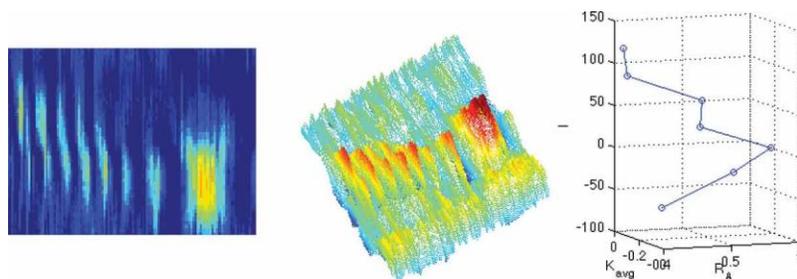
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Fig. 15. Stripmap SAR image and its K-R-I curve, damaged side, $\theta = 25$ -deg.



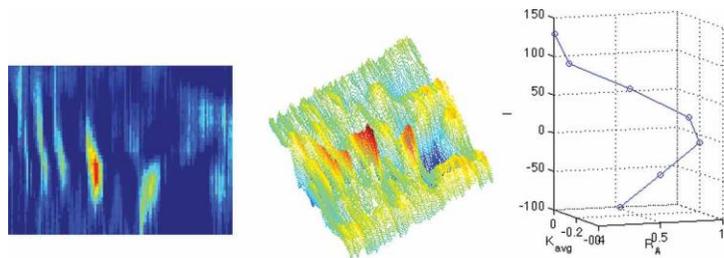
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Fig. 16. Stripmap SAR image and its K-R-I curve, intact side, $\theta = 30$ -deg.



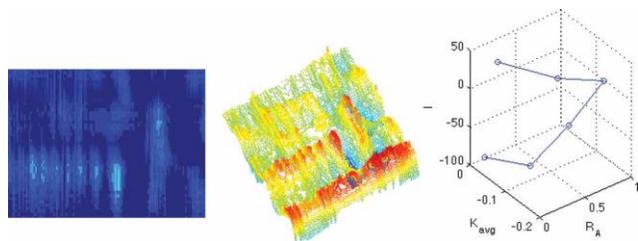
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Fig. 17. Stripmap SAR image and its K-R-I curve, damaged side, $\theta = 30$ -deg.



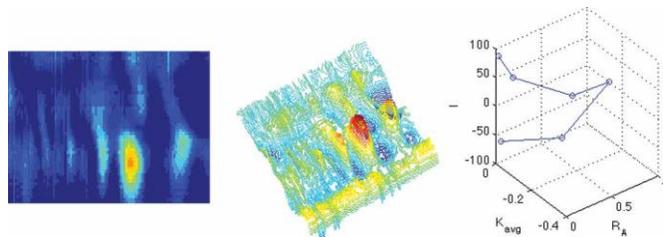
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Fig. 18. Stripmap SAR image and its K-R-I curve, intact side, $\theta = 45$ -deg.



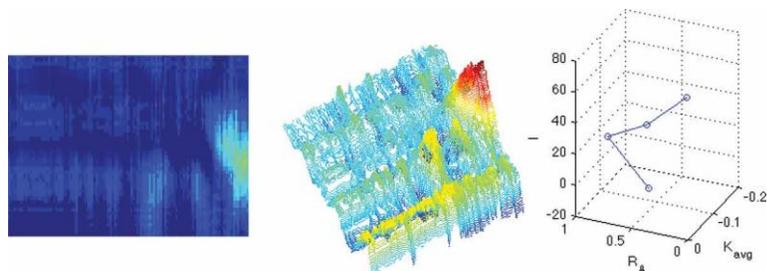
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Fig. 19. Stripmap SAR image and its K-R-I curve, damaged side, $\theta = 45$ -deg.



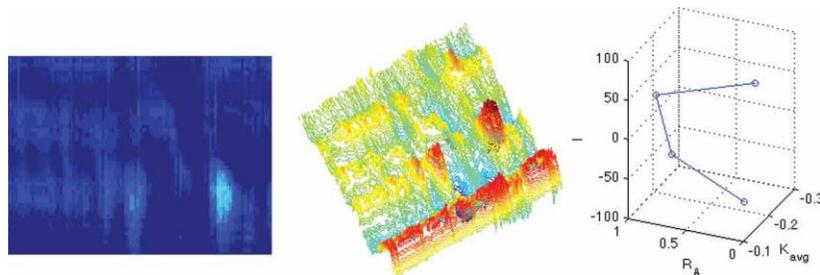
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Fig. 20. Stripmap SAR image and its K-R-I curve, intact side, $\theta = 60$ -deg.



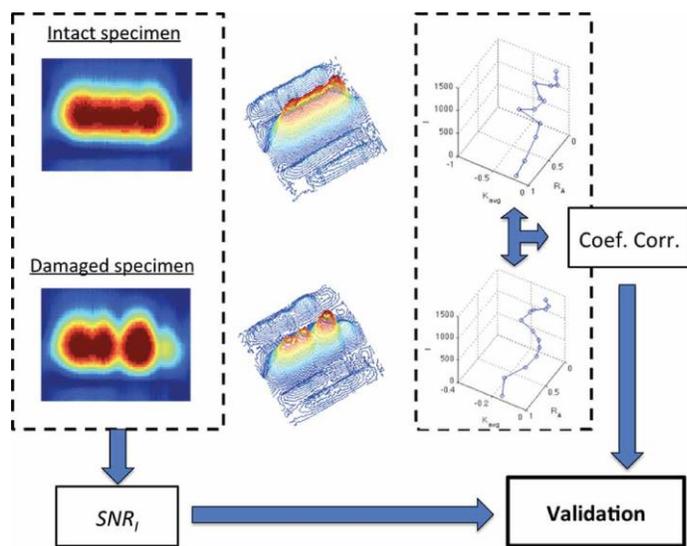
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Fig. 21. Stripmap SAR image and its K-R-I curve, damaged side, $\theta = 60$ -deg.



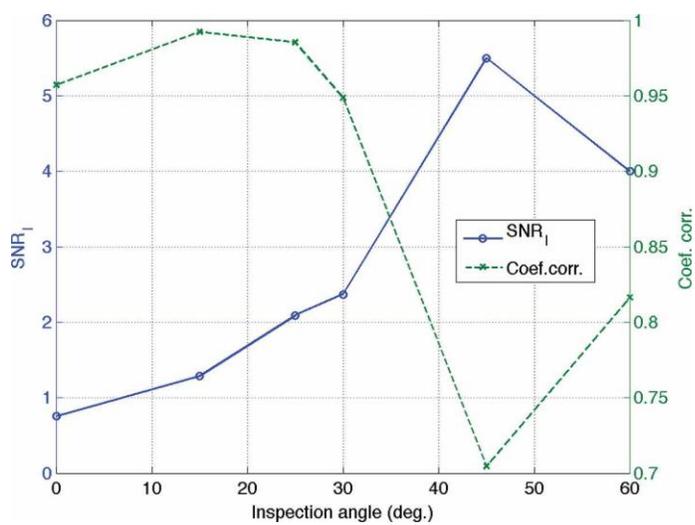
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Fig. 22. Schematic of a forward study for algorithm validation



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Fig. 23. Comparison between traditional SNR approach and the K-R-I representation of SAR images



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Table 1. Performance comparison between the K-R-I curves and the SNR_I of SAR images

Inspection angle	Background (or noise) (I_{int})	Target signal (I_{dam})	SNR_I	Coef. corr.
0-deg.	913	1,209	0.7552	0.9571
15-deg.	643	499	1.2886	0.9923
25-deg.	230	110	2.0909	0.9854
30-deg.	165.9	70	2.3700	0.9487
45-deg.	110	20	5.5000	0.7045
60-deg.	40	10	4.0000	0.8164