Changing flight heading during pass to enhance SAR change detection performance

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Abstract
Due to the wavelength-resolution characteristics, wavelength-resolution synthetic aperture radar (SAR) is considered for the change detection application aiming to achieve high detection probability and low false alarm rate. However, wavelength-resolution SAR change detection suffers from the problems caused by specular reflection of the elongated structure in the SAR scene, the dependency of radar cross-section on incident angle of electromagnetic wave, the interference due to antenna backlobe and so forth. Hardware and software solutions are therefore desired to deal with these problems. The authors propose to change flight heading during passes as a natural solution. The proposed solution is tested with the CARABAS data using a typical SAR change detection method. The achieved change detection results show the good performance of the proposed solution, for example, the detection probability is up to 100% with the false alarm rate of 0.5 per square kilometre.

1 INTRODUCTION

Synthetic aperture radar (SAR) change detection has been researched for decades and is still an active research area [1–7]. It allows the detection of changes in a ground scene between two measurements separated in time. The changes can be the result of, for example, natural disasters, humans’ legal and illegal activities. For detecting changes, first, the SAR data retrieved from two different measurements are used to form the images of the ground scene, namely, reference and surveillance images. Then, an algorithm runs on these reference and surveillance images and marks the positions where the changes might be present, and where there is no change. Finally, morphological operators, such as erosion and dilation, are applied to the detection results for minimising the false alarm rate. Therefore, a change detection method can be designed in the following sequence: image formation, detection and classification. Although the research on SAR change detection usually focuses on the detection step, recently, some research on classification using, for example, machine learning, is of interest [8–10].

Among SAR change detection methods, the ones developed for wavelength-resolution SAR are dominant because of the beneficial characteristics of the wavelength-resolution SAR. For wavelength-resolution SAR, the contribution of small scatterers to backscattering is negligible as a result of radar wavelengths of several metres. The main contribution to radar response comes from big scatterers with metre size or larger. Such big scatterers are usually very stable in time. This characteristic feature is different from conventional SAR systems in which the contribution of small scatterers like tree leaves cannot be neglected. The change detection methods developed for wavelength-resolution SAR are also very diverse. The theories, such as Neyman-Pearson lemma and Bayes’ theorem, can be used for the method development [11–17]. Different probability distributions for random variables to model the distribution of clutter and noise present in SAR images are also available. Their probability density functions support calculating the likelihood ratio test (Neyman-Pearson lemma) and the conditional probability (Bayes’ theorem). A typical change detection method, that will be used later in this article, has been developed using the Neyman-Pearson lemma, in which the likelihood ratio test was derived with the bivariate Rayleigh probability density function. Although the method is simple, it can provide very good change detection results with high detection probability and low false alarm rate. However, there are also technical
problems with wavelength-resolution SAR change detection that have been stated in some publications.

The first problem concerns the dependency of radar cross section on incident angle of electromagnetic wave. As stated in the publications [14, 16–18], target backscattering depends strongly on target orientation and/or flight heading. The radar cross-section of a target is large or small depending on how it is oriented and how the flight heading is set up. This leads to the case that a target with large dimensions can result in a small radar cross-section. In this case, it is most likely that the SAR change detection methods fail to detect the target. The second problem comes from the elongated structures in ground scenes, such as power lines, fences and very large buildings that can cause specular reflections. The SAR change detection methods usually classify these structures to be a target that contributes to false alarm rate. The third problem originated from the antenna backlobe. The wavelength-resolution SAR systems use omnidirectional antennas, such as dipoles, for synthesising long apertures. Therefore, the radar responses are not only from the ground scene of interest but also from other unwanted sources. This causes coherent interference present in SAR data, consequently, pseudo targets in images and false alarms for SAR change detection. In addition, there might also be other problems with wavelength-resolution SAR change detection that have not been recognized yet. However, the mentioned problems can make the performance of a change detection method drop sharply below its average performance. In practice, the SAR change detection methods [14, 16, 17] can work well with most of the data but these methods give bad change detection results for few data.

Some approaches for the declared problems can be found in recent publications. For example, an adaptive signal processing mechanism, namely adaptive noise canceller, is used to adaptively estimate the clutter present in images and exclude it from the images [18]. By this, the false alarms caused by the elongated structures in a ground scene can be reduced significantly. The main disadvantage of this approach is the requirement about three SAR images that might not be fulfilled in practice. The method requires three SAR images associated with three measurements, with no change between two of them. A comprehensive hardware and/or software solution for the stated problems are therefore still desired.

Here, we propose to change flight heading during passes as a natural solution. Instead of keeping the flight heading constant during passes, we can set up two or more flight headings for every pass. The solution is supposed to have the capability to solve the declared problems, that is, specular reflection, weak radar cross-section due to incident angle, and the antenna backlobe issue. It is common knowledge that the radar cross-section of a target, including elongated structures, will be changed if there is a change in the incident angle. The small radar cross-section, specular reflection, and/or the backlobe issue associated with a certain flight heading can therefore be minimised. Using the SAR systems with circular tracks can be another solution [19, 20]. However, increasing the aperture to 360° will reduce the area coverage rate, increase the processing complexity, including managing the topography. In addition, there will be more demanding requirements of the geometrical accuracy. Changing flight heading during passes proposed in this article might also lead to new challenges, for example, motion compensation due to the difficulty in physical adaptation of flight path, coherency due to long integration time and unknown problems. The solution may only be applied to airborne systems including aircraft platform, for example, CARABAS-II, and helicopter platform, for example, CARABAS-III, in which changing the flight heading during passes is feasible.

The rest of the paper is organised as follows: Section 2 presents the change detection method, which will be used in this study. The section also introduces the approach for the stated problems. Section 3 provides the experimental results. The further discussions are given in Section 4. Section 5 presents conclusions.

2 | CHANGE DETECTION

As mentioned in the introduction, the processing sequence of a change detection method can include image formation, detection and classification. Since the approach for the stated problem is based on changing the flight heading during passes, the image formation step plays an important role in a change detection method. Among SAR image formation algorithms, only time-domain SAR image formation algorithms can handle the SAR data collected along the track with two or more flight headings. Once the reference and surveillance images are formed, a method can be used for detecting changes.

2.1 | SAR image formation

It can be a difficult task to use the SAR image formation algorithm processing in frequency-domain to form an image from the SAR data collected along a non-linear track as illustrated on the left-hand side of Figure 1. However, this task can
be handled easily with the algorithms processing in time-domain, for example back-projection [21]. A back-projection process is interpreted by the spherical projection of the radar signal on a ground-range plane. A complex image \( b(\xi, \eta) \) is formed by superposing of the back-projected radar signal collected along aperture. This process can be expressed by the integral:

\[
b(\xi, \eta) = \int_{t_{\text{start}}}^{t_{\text{stop}}} g(t, \tau) dt
\]

where \( t_{\text{stop}} - t_{\text{start}} \) represents the synthetic (integration) time, \( g(t, \tau) \) is the radar signal, \( t \) and \( \tau \) are the azimuth and range time, respectively. The range time is calculated by the ratio of the two times range to the speed of wave propagation, in which the range is calculated from the SAR geometry. The range is also the radius for spherical back-projection:

\[
\tau = \frac{2r}{c_0} = \frac{2}{c_0} \sqrt{(\xi - x(t))^2 + (\eta - y(t))^2 + z(t)^2},
\]

where \( (x, y, z) \) denotes the aperture position and also is the sphere centre, \( (\xi, \eta) \) denotes the image coordinate, and \( z(t) \) is the flight altitude and is usually a constant, and \( c_0 \) is the speed of wave propagation.

As illustrated on the left-hand side of Figure 1, the operation of the back-projection algorithm is independent of the topology of flight track (line or curve). We can always calculate the range \( r \) corresponding to a specific aperture position \( (x, y, z) \) and a specific image coordinate \( (\xi, \eta) \). For this reason, a back-projection algorithm can be used for non-linear flight tracks, such as circular tracks and the flight tracks that motion error compensation methods cannot manage. To save the processing time of the back-projection process, the algorithms, such as fast back-projection or factorized fast back-projection, can be used, in which the back-projection process is implemented for subaperture and/or subimage. However, there is always a trade-off between processing time and image quality.

The proposed solution is illustrated in the right-hand side of Figure 1. Instead of keeping the SAR platform following the trajectory with a constant flight heading angle (dashed line), we can set up a flight trajectory that is composed of two linear parts with two different flight heading angles (solid line). In the middle part (dotted-dashed curve) of the trajectory, there is no data collection. As illustrated, the targets and clutter in the ground scene will be observed by two different angles. By this, the stated problems, that is, specular reflection, small radar cross-section associated with a certain incident angle, and the antenna backlobe issue, can be minimised. In the SAR image formation process, the superposing of back-projected radar signal collected along a radar aperture is expressed by the integral

\[
b(\xi, \eta) = \int_{t_{\text{start}}}^{t_1} g(t, \tau) dt + \int_{t_2}^{t_{\text{stop}}} g(t, \tau) dt
\]

where the integration time is unchanged and given by

\[
(t_3 - t_2) + (t_1 - t_{\text{start}}) = t_{\text{stop}} - t_{\text{start}}
\]

2.2 Detection

For simplicity and with a focus on the proposed solution, the discussion about change detection presented in this article is limited by the incoherent case, that is, change detection is based on only the modulus or magnitudes of images (reference and surveillance or updated), whereas the phase information is ignored.

2.2.1 Likelihood ratio test

In the change detection context, Neyman-Pearson lemma is interpreted as follows. When performing a hypothesis test between two hypotheses, change between two measurements \( \langle H_1 \rangle \) and no-change between two measurements \( \langle H_0 \rangle \), the likelihood ratio test which rejects the hypothesis \( H_0 \) is in favour of hypothesis \( H_1 \)

\[
\Lambda(|h|) = \frac{P(|h|\|H_1 \rangle)}{P(|h|\|H_0 \rangle)} > \lambda
\]

where

\[
|h| = \begin{bmatrix} |b_x(\xi, \eta)| \\ |b_y(\xi, \eta)| \\ |s_r + c_r + n_r| \end{bmatrix} = \begin{bmatrix} |s_x + c_x + n_x| \\ |s_y + c_y + n_c| \\ |s_r + c_r + n_r| \end{bmatrix} = \begin{bmatrix} |s_x + c_x + n_x| \\ |s_y + c_y + n_c| \end{bmatrix}
\]

The subscripts \( r \) and \( u \) in (6) refer to the surveillance and reference images, respectively. Herein, an image pixel is assumed to contains target (change) \( s \), clutter \( n \), and noise \( r \). To detect new targets appearing in the surveillance image, the reference image is assumed to contain only clutter and noise. Hence, we can set \( s = 0 \), whereas \( s = 0 \) for the hypothesis \( H_0 \) and \( s = 0 \) for the hypothesis \( H_1 \). The probability \( P(|h|\|H_0 \rangle) \) can be calculated directly from an appropriate probability density function of the clutter and noise distribution while it is also possible to calculate \( P(|h|\|H_1 \rangle) \) using the same probability density function. Hence, if we can exclude all the targets from the surveillance image, the rest contains only clutter and noise. This can be done by a simple subtraction, that is, \( P(|h|\|H_1 \rangle) = P(|h - s|\|H_0 \rangle) \). Therefore, the likelihood ratio test can be written the following form

\[
\Lambda(|h|) = \frac{P(|h - s|\|H_0 \rangle)}{P(|h|\|H_0 \rangle)} > \lambda
\]

We can also exchange the roles of reference and surveillance in the likelihood ratio test to detect the targets that disappear from the surveillance image.
2.2.2 | Bivariate Rayleigh distribution

For the case, where the clutter and noise present in the images are modelled by a Rayleigh distribution, the probability distribution for \( P(|\mathbf{h}||H_0) \) is given by the probability density function of a bivariate Rayleigh distribution:

\[
P(|\mathbf{h}||H_0) = \frac{|b_u||b_v|}{\sigma_u^2 \sigma_v^2 (1 - \rho)} I_0 \left( \frac{\sqrt{\rho}}{1 - \rho} \frac{|b_u||b_v|}{\sigma_u \sigma_v} \right) \times \exp \left\{ -\frac{1}{1 - \rho} \left( \frac{|b_u - s_u|^2}{2 \sigma_u^2} + \frac{|b_v|^2}{2 \sigma_v^2} \right) \right\} \tag{8}
\]

where \( \rho \) is the correlation coefficient, \( \sigma_u \) and \( \sigma_v \) are the scale parameters of the bivariate Rayleigh distributions, \( I_0(\cdot) \) is the modified Bessel function of the first kind. Therefore, the probability distribution for \( P(|\mathbf{h}||H_1) \) will be given as:

\[
P(|\mathbf{h}||H_1) = \frac{|b_u - s_u||b_v|}{\sigma_u^2 \sigma_v^2 (1 - \rho)} I_0 \left( \frac{\sqrt{\rho}}{1 - \rho} \frac{|b_u - s_u||b_v|}{\sigma_u \sigma_v} \right) \times \exp \left\{ -\frac{1}{1 - \rho} \left( \frac{|b_u - s_u|^2}{2 \sigma_u^2} + \frac{|b_v|^2}{2 \sigma_v^2} \right) \right\} \tag{9}
\]

Substituting (8) and (9) into (7), we obtain the following statistical hypothesis test [16]:

\[
\Lambda(|\mathbf{h}|) = \frac{|b_u - s_u|}{|b_u|} \times \exp \left\{ -\frac{1}{1 - \rho} \left( \frac{|b_u - s_u|^2}{2 \sigma_u^2} - \frac{|b_v|^2}{2 \sigma_v^2} \right) \right\} \times I_0 \left( \frac{\sqrt{\rho}}{1 - \rho} \frac{|b_u - s_u||b_v|}{\sigma_u \sigma_v} \right) \left[ I_0 \left( \frac{\sqrt{\rho}}{1 - \rho} \frac{|b_u||b_v|}{\sigma_u \sigma_v} \right) \right]^{-1} \tag{10}
\]

It is worth mentioning that several practical issues, such as parameter estimation, the assumptions about targets and the calculations for Bessel function, should be considered when calculating the statistical hypothesis test (10) [22].

For parameter estimation, it is not easy to obtain an optimum scale parameter set for the bivariate Rayleigh distribution since a Rayleigh distribution belongs to the single parameter family of probability distributions. As shown in [22], a mismatch between the data histogram and the probability density function occurs, especially surrounding the peak frequency and the tail of the data histogram. If the parameter is estimated by the maximum likelihood method, there will be a mismatch surrounding the peak frequency. This mismatch is caused by the targets present in the SAR scene. To avoid this problem, the local frequency method is recommended for estimating the scale parameters.

As seen in Equations (7) and (10), an assumption about target, that is, \( s_u \), must be made to calculate the statistical hypothesis test. According to the reverse triangle inequality of complex numbers, we always have

\[
|b_u| - |s_u| = |b_u - s_u| \geq |b_u| - |s_u| \tag{11}
\]

Equation (11) implies that we should select the target magnitude \( |s_u| \) for computing the statistical test smaller or equal than the true magnitude of target \( |s_u| \). Since \( |b_u - s_u| \geq 0 \), an assumption about \( |s_u| \) must fulfill the condition \( |s_u| \leq |b_u| \). This leads to the case, in which the image pixels, that do not fulfill this condition, will be excluded from the statistical hypothesis test and are assigned by the hypothesis \( H_0 \). The assumption about the target magnitude for computing the statistical test can now be switched to the assumption about \( P(|b_u| < |s_u|) \) by using the cumulative distribution function of a Rayleigh distribution

\[
|s_u| = \sigma_u \sqrt{2 \ln \left( \frac{1}{1 - P(|b_u| < |s_u|)} \right)} \tag{12}
\]

In practice, the assumptions on the target magnitude \( s_u \) are not very sensitive to the change detection results and this is an advantage of using a bivariate Rayleigh distribution for the statistical hypothesis test [22].

The modified Bessel function of the first kind \( I_0(\cdot) \) in (10) is a monotonically increasing function. In the case where the scale parameters are small while the correlation coefficient is close to unity, the function might approach infinity rapidly and consequently, this causes trouble for computing the statistical hypothesis test. However, since \( |b_u| - |s_u| \approx |b_u - s_u| \leq |b_u| \), the modified Bessel function in the denominator in (10) approaches infinity faster than the one in the numerator. For the very large values given by the modified Bessel functions, that can be outside the calculation range of computer, we can assign the testing pixels to the hypothesis \( H_0 \).

2.2.3 | Thresholding

After performing the statistical hypothesis test, we get a matrix with the values given by (10). The dimensions of the statistical hypothesis test matrix are identical to the dimensions of the reference and surveillance images. A universal detection threshold \( \lambda \) is applied to this matrix. The elements of the matrix with the values larger than the set threshold \( \lambda \) are supposed to possibly contain the changes and conversely, the elements with the values smaller than the threshold \( \lambda \) are determined as containing no change. By setting \( '1' \) to change and \( '0' \) to no change, we get a binary change detection matrix.

2.3 | Classification

To minimise the false alarm rate, it is reasonable to use the morphological operations such as erosion and dilation. For erosion, the detections that do not match certain requirements
on structuring element will be classified to be false alarms. It is quite often that a rectangular element associated with the azimuth and range resolutions is utilised for erosion. In this case, the detections with dimensions smaller than the spatial resolutions will be classified as the false alarms. For dilation, we locally merge the adjacent detections to form the detections with larger dimension. In the case where the same structuring element for erosion can be utilised for dilation, the adjacent detections separated less than the spatial resolutions will be merged.

In practice, other structuring elements can also be designed according to purposes. For example, if the dimensions of targets of interest are known, the structuring elements for erosion and dilation should be designed according to the known dimensions.

### 3 | EXPERIMENTAL RESULTS

In this section, we provide some experimental results to examine and evaluate the solution proposed in Section 2. We do not have exactly the required data to examine the solution, but we can create the examining data from the available CARABAS data somehow. The most important is that we have the data, in which the stated problems, such as the dependency of radar cross-section on the incident angle of the electromagnetic wave and the interference originating from antenna backlobe, are present.

#### 3.1 | Data description

In 2002, a measurement campaign was performed with CARABAS-II system in northern Sweden [14]. The goal of the measurement was to achieve the data for SAR change detection research. One of the important outcomes is the 24 pairs of reference and surveillance SAR images that had been spatially and radiometrically co-registered. The images cover a ground area of 3000 × 2000 m. The magnitudes of the images are stored in the matrices whose rows and columns correspond to azimuth and range, respectively. With the image pixel 1 × 1 m, the matrices have 3000 rows and 2000 columns.

In the ground scene, the military vehicles (trucks and vans) were differently deployed at four locations and with four different orientations. The dimensions of the vehicles are 4.4 × 1.9 × 2.2 m, 6.8 × 2.5 × 3.0 m and 7.8 × 2.5 × 3.0 m (length × width × height). Each mission referring to a specific target orientation and a specific location deployed in the ground. There were four missions (II, III, IV and V), and each mission was measured by six different passes (1, 2, 3, 4, 5 and 6). These passes used three flight headings, in which passes 1 and 3 are identical, passes 2 and 4 are identical, and passes 5 and 6 are identical. Table 1 summarises the main information concerning the measurement campaign.

| Mission | Orientation | Location | Pass | Heading |
|---------|-------------|----------|------|---------|
| II      | 225°        | Upper right | 1    | 225°    |
| III     | 315°        | Upper right | 2    | 135°    |
| IV      | 225°        | Lower left  | 3    | 225°    |
| V       | 270°        | Lower left  | 4    | 135°    |
|         |             |           | 5    | 230°    |
|         |             |           | 6    | 230°    |

Among 24 pairs of reference and surveillance images, the pair associated with mission III, mission V and pass five is challenging for all available change detection methods developed for wavelength-resolution SAR. Either the detection probability is extremely low, or the false alarm rate is extremely high in comparison to the average detection probability and false alarm rate obtained with the methods. It is worth to highlight that the metrics for evaluating a change detection method are detection probability ($P_D$) and the false alarm rate. The former is the ratio of the number of detected targets to the number of the deployed targets given in percentage and the latter is calculated by the number of counted false alarms divided by the area. For the considered CARABAS data, the number of deployed target is 25 and the area is 6 km².

The first part of Table 2 (from top to the first extra line) provides the average change detection results provided by the methods [16, 17]. With the false alarm rate of 0.5 false alarm per km², the detection probabilities provided by both the methods are more than 90%.

The change detection performance of the methods with the challenging pair denoted by III-5 and V-5 is provided in the second part of Table 2 (from the first extra line to the second extra line). The degradation can be seen by comparing the average values (2 experiments) and the average values given
in the first part of the table (24 experiments). As seen, the detection probability drops about 15% (e.g., 80\% \(\geq\) 97\%) while the false alarm rate increases up to 6 times (e.g., 0.50 \(\geq\) 3.26). The degradation has been proved to be caused by the stated problems including the specular reflections of the elongated structures in a SAR scene and the dependency of radar cross-section on the incident angle of electromagnetic wave. The interference originating from the antenna backlobe is not observed in this challenging pair.

To confirm the statement about degradation, the third part of Table 2 (from the second extra line to the third extra line) provides the change detection results performed on another pair with the same mission (III and V) but different pass (2). The flight heading is now changed from 230 to 135° and the change detection results are improved significantly and similar to the average detection results given in the first part of the table (24 experiments).

### 3.2 Data processing

The proposal introduced in Section 2 requires a data acquisition including two different flight headings. As mentioned in Section 2, the image formation with the data acquired along a flight track with two flight headings is easily handled by the back-projection algorithm. Although we do not have such raw data, we can still create required SAR images for examining the proposal from the available challenging pair of reference and surveillance images and some other available pairs.

#### 3.2.1 Data formation

Here we propose to superpose two images belonging to the same mission (target orientation and location) but associated with different passes (flight heading). Since the provided CARABAS data is magnitude images, the superposition will be performed by an addition and this might lead to the problem of coherency. However, it is not a problem for incoherent change detection, as shown in the following experiments.

The images associated with pass 2 are selected to add to the images associated with pass five in order to create the data for examining the proposal. The flight heading of pass 2 is 135° that is totally different from the flight heading of pass 5. Hence, the created data belongs to missions III and V, and associated with passes 2 and 5. They are denoted in the fourth part of Table 2 by III-2 + III-2 and V-5 + V-2.

Figure 2 shows the created data from the SAR images belonging to mission V and associated with pass 2 + 5. For this mission, the military vehicles (trucks and vans) were deployed in the lower left of the image. We can observe then in Figure 2 although they are obscured by foliage.

#### 3.2.2 Experiment 1: Rayleigh

In the first experiment, the created data belonging to mission III is selected for the reference image. The other (mission V) will play the role of surveillance image. We calculate the magnitude for the targets using (12) and get \(|\tilde{t}_a| = 0.4\).
Armed with this assumption, we calculate the statistical hypothesis tests using (10) for all \([b_h(\xi, \eta)]\) that meet the demands \(|b_h(\xi, \eta)| \geq 0.4\), and in the calculation range of Bessel function \(I_0(\cdot)\). The Statistical hypothesis test will provide the values of \(\Lambda(h)\) of all pairs of pixels in the matrix form.

A detection threshold is universally applied to the matrix \(\Lambda(h)\). The thresholding step results in a binary matrix so that the element of the matrix gets the value 1 if \(\Lambda(h) \geq \lambda\) and 0 if \(\Lambda(h) < \lambda\). In other words, the value 1 corresponds to a possible change and the value 0 means that there is no change.

The range of detection threshold can be estimated approximately based on the assumption on target \(s_u\). The lower bound is given by the ratio of \(\Lambda\left(\left[\sigma_u \sqrt{\pi/2}, \sigma_r \sqrt{\pi/2}\right]^T\right)\) to \(\Lambda\left(\left[\sigma_u \sqrt{\pi/2} + s_u, \sigma_r \sqrt{\pi/2} + s_u\right]^T\right)\), whereas the upper bound is given by the ratio of \(\Lambda\left(\left[s_u, s_u\right]^T\right)\) to \(\Lambda\left(\left[2s_u, 2s_u\right]^T\right)\). We can also estimate experimentally by setting the lower bound so that the detection probability of 100% is reached, and the upper bound so that there is no false alarm. For the experimental purpose, we use the later approach and get a wide range of detection thresholds \(\lambda \in [10^{12}, 10^{24}]\). In this experiment, the detection threshold is set by \(\lambda = 10^{13}\). This is understood that if the probability of the hypothesis \(H_1\) calculated for a surveillance image pixel and the corresponding reference image pixel is higher or equal to \(10^{13}\) times than the probability of the hypothesis \(H_0\), then the surveillance image pixel is assumed to possibly contain a change. Otherwise, it contains only clutter and noise.

To minimise false alarms, we remove the isolated detections whose dimensions are below the spatial resolutions and locally link the adjacent detections after removal. The spatial resolution of the original CARABAS images achieved with this measurement campaign is about 3 m. However, when we add the images to create the data for examining the proposal, the resolution will be enhanced. An investigation on spatial resolutions suggests that the spatial resolution is improved to about 2 m. The structuring element for erosion operator can therefore be selected by 2 pixels. The dilation operator relates to the targets. For this reason, applying three dilation operators after the erosion operator with the same structuring element is reasonable.

The change detection results are reported in the fourth part of Table 2 (from the third extra line to the fourth extra line) and Figure 3. In Figure 3, the detected targets are marked by the white rectangle, whereas the false alarms are marked by the white circles. In this experiment, there are 25 detections that can be related to 25 vehicles deployed for mission III. They are classified as the detected targets and the detection probability is therefore 100%. There are six detections that do not relate to the deployed targets. They will be classified as false alarms. Converting to the false alarm rate by dividing this number (6) to the area of 6 km², we get the rate of 1.00 false alarm per square kilometre.

Comparing the new change detection results reported in the fourth part and the old ones in the second part of Table 2, we can see that the change detection performance of the proposal with this challenging pair is enhanced significantly and is about the average performance (24 experiments) reported in the first part of Table 2.

3.2.3 | Experiment 2: Rayleigh

In the second experiment, we exchange the roles of reference and surveillance that have been assigned in the experiment 1. We keep the same parameters including \(|\bar{s}_u| = 0.4, \lambda = 10^{13}\), the structuring element for the morphological operators 2 m and the morphological operators. The change detection results are also reported in the fourth part of Table 2. In this experiment, all detections can be related to the 25 vehicles deployed for mission III and classified to be detected targets. The detection probability is therefore 100% and there is no false alarm.

The average values of detection probability and false alarm rate of the experiments 1 and 2 are given in the last row of the fourth part of Table 2 and they are even better than the average ones obtained with 24 experiments reported in the first part of Table 2. This is explained partially where the proposal is able to solve the stated problems efficiently. On the one hand, the specular reflections of the elongated structures in the SAR scene and the dependency of radar cross-section on the incident angle of the electromagnetic wave have been minimised. On the other hand, this improvement in change detection performance can come from the improvement in the spatial resolutions. This will lead to a question about the effects of the spatial resolutions on the change detection results that will be addressed in the next section.

3.3 | Evaluation

For evaluating the proposal, we look at the effects of spatial resolutions on the change detection performance and retrieve a receiver operating characteristic (ROC) curve. We use the same principle that has been used to create the examining data and to create the data for evaluation.

3.3.1 | Effects of spatial resolutions

To evaluate the effects of the spatial resolutions on change detection results, we create the data by adding the images associated with pass 5 and pass 6. The flight heading of pass 6 is 230° and is identical to the one of pass 5. Hence, the created data for evaluation belongs to missions III and V, and is associated with flight heading 5 and 6. They are denoted in the last part of Table 2 (from the fourth extra line to the bottom) by III-5 + III-6 and V-5 + V-6.

The method parameters used in experiments 1 and 2 are reused for evaluation, that is, \(|\bar{s}_u| = 0.4, \lambda = 10^{13}\), the
structuring element for morphological operators is 2 m, and the morphological operators include erosion and dilation.

In the case where the created data belonging to mission III is selected for the reference and the other (mission V) for the surveillance, the considered detection method can detect 25 among 25 vehicles deployed for mission III. A detection probability of 100% is achieved. There are 10 detections that cannot be related to any deployed target. They are classified as false alarms. The number of false alarms gives a false alarm rate of 1.67 false alarm per square kilometre. All false alarms originate from the power lines (elongated structures) on the left-hand side of the imaged ground scene. Comparing to the change detection results reported in the second part of Table 2, we can observe the enhancement in change detection results brought by the higher spatial resolutions.

If we exchange the roles of the reference image and the surveillance image, 21 among 25 vehicles deployed for mission III are detected and there is one false alarm. This corresponds to a detection probability of 84% and a false alarm rate of 0.33 false alarm per square kilometre.

The average change detection results are also reported in the last part of Table 2. Comparing them to the change detection results provided by the proposal given in the fourth part of Table 2, we can still see the gaps between the results.

3.3.2 | Receiver operating characteristic

We can further evaluate the proposal and also the effects of spatial resolutions by changing the threshold $\lambda$ in the range $\lambda \in [10^{12}, 10^{21}]$. Each threshold in the range will provide an average detection probability with respect to an average false alarm rate. By this, the range of thresholds generates the receiver operating characteristic (ROC) curves.

Figure 4 shows four different ROC curves, in which two curves are extracted from [17] (likelihood ratio test derived from bivariate gamma distribution) and [22] (likelihood ratio test derived from bivariate Rayleigh distribution). Among two extant curves, one is obtained with the examining data created for experiments 1 and 2. The other is obtained with the created data for evaluating the effects of spatial resolutions on change detection performance. From the figure, we can draw some comments on the results, which are as follows.
According to (4), there is a period $t_2 - t_1$ with no data acquisition. For incoherent change detection presented in Section 3, this period has no significant effect on change detection performance. However, for coherent change detection, this period might be a problem. However, it should be highlighted that the SAR geometry was proposed in this study partially motivated by the available data set so that the period with no data acquisition had been included. In practice, it is unnecessary to have such the period. A SAR system can collect the data continuously without interruption, that is, collect the data even in the period $t_2 - t_1$. For the time-domain image formation algorithms such as the back-projection algorithm, there is no problem to handle the non-linear aperture sketched in Figure 1 or other non-linear apertures such as circular aperture.

Another advantage of the back-projection algorithm is that the algorithm can compensate the motion errors efficiently. As shown in [18], the requirement about the similarity of flight paths is not very strict for wavelength-resolution SAR change detection. These features help to deal with the difficulty in physical adaptation of flight paths.

4.2 | Change detection methods

We can use any available approach for detection and any available approach for classification. For example, if we model the clutter and noise present in SAR images by a bivariate gamma distribution, we can derive another statistical hypothesis test by [17]:

$$
\Lambda(z) = \left(\dfrac{|b_u - s_u|}{|b_u|}\right)^{k-1/2} \exp\left\{ -\dfrac{1}{1 - \rho} \left(\dfrac{|b_u - s_u| - |b_u|}{\theta_u}\right) \right\} 
\times I_{k-1}\left(\dfrac{2}{1 - \rho} \sqrt{\dfrac{|b_u - s_u|}{|b_u|}} \right) 
\times \left[ I_{k-1}\left(\dfrac{2}{1 - \rho} \sqrt{\dfrac{|b_u - s_u|}{|b_u|}} \right) \right]^{-1}
$$

for the case where the reference image and surveillance image share the same shape parameters, that is, $k = \kappa = k$, but have different scale parameters, that is, $\theta_u \neq \theta_r$. Since a gamma distribution belongs to a two-parameter family of probability distributions (Rayleigh requires only a single scale parameter), this increases the adaptability and flexibility of the gamma probability density function to the data histogram.

We can see the similarity between (10) and (13), in which the statistical hypothesis tests contain the assumption on target $s_u$, scale parameters and modified Bessel functions. The practical issues considered in calculating the statistical hypothesis test (10) should be considered in calculating the statistical hypothesis test (13). The assumption on target magnitude is based on the cumulative distribution function of a gamma distribution

$$
P(|b_u| < |s_u|) = \dfrac{1}{\Gamma(k)} \gamma\left( k; \dfrac{|s_u|}{\theta_u} \right)
$$

where $\gamma(\cdot)$ is the lower incomplete gamma function. By setting $P(|b_u| < |s_u|)$, $|s_u|$ can be retrieved, and then $|s_u|$ can be assumed using the reverse triangle inequality (11).

For this discussion, we keep the same parameters that have been used in experiments 1 and 2, that is, $|s_u| = 0.4$, $\lambda = 10^{13}$, the structuring element for morphological operators is $2 \times$ and
the morphological operators include erosion and dilation. We only replace the statistical hypothesis test (10) by (13) in the processing sequence. Armed with the model and the parameters, we get an average detection probability of 100% and the false alarm rate of only 0.08 false alarm per square kilometre as reported in the fourth part of Table 2.

5 | CONCLUSION

The paper has proposed a natural and simple solution for the problems caused by the specular reflection of elongated structures in a SAR scene, the dependency of radar cross-section on the incident angle of the electromagnetic wave, the interference originated from the antenna backlobe and so forth. The proposed solution is based on changing flight heading during a single pass. By this, specular reflection, weak radar cross-section due to incident angle, and the issues caused by antenna backlobe can be minimised. The proposal is examined with the data formed from the available CARABAS data. The experiments show an increase in the detection probability and a decrease in the false alarm rate simultaneously and significantly. For example, the detection probability increases from 80% to 100%, whereas the false alarm rate decreases from 3.26 to 0.50 false alarm per square kilometre. Such enhancements are significant. However, the targets deployed in the measurement campaign were size-specified rectangles. For other shape-targets, the structuring element for the morphological operators might need to be modified. The proposed solution can widely use other available change detection methods as shown in the discussion section of the paper.

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