Adaptive Change Detection in Coherent and Noncoherent SAR Imagery

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SUMMARY

This paper is concerned with change detection in averaged multi-look SAR imagery. Averaged multi-look SAR images are preferable to full aperture SAR reconstructions when the imaging algorithm is approximation based (e.g., polar format processing), or motion data are not accurate over a long full aperture. We study the application of a SAR change detection method, known as Signal Subspace Processing, that is based on the principles of 2D adaptive filtering [13], [14]; and we use it to recognize the addition of surface landmines to a particular area under surveillance. We identify the change detection problem as a trinary hypotheses testing problem, and identify a change signal and its normalized version to determine whether there is i) no change in the imaged scene; ii) a target has entered the imaged scene; or iii) a target has exited the imaged scene. A statistical analysis of the error signal is provided to show its properties and merits. Results are provided with a realistic X band SAR platform using averaged noncoherent multi-look and coherent single-look SAR imagery.

1. *INTRODUCTION*

Modern Synthetic Aperture Radar (SAR) signal processing algorithms could retrieve accurate and subtle information regarding a scene that is being interrogated by an airborne radar system. An important reconnaissance problem that is being studied via the use of the SAR systems and their sophisticated signal processing methods involves detecting changes in an imaged scene. In these problems, the user interrogates a scene with a SAR system at two different time points [9] (e.g., different days); the resultant two SAR databases, that we refer to as *reference* and *test* data, are used to determine where targets have entered or left the imaging scene between the two data acquisitions. For instance, FOPEN (FOliage PENetrating) VHF/UHF SAR systems are being studied to detect movements of concealed military vehicles in foliage [15]. Furthermore, X band SAR systems have the potential to become a potent tool to determine whether mines have been recently deployed in an area [6].

The basic idea in these reconnaissance problems is to *compare* the reference and test SAR images to identify/detect changes [9]. However, the practical implementation of such a comparison requires understanding and incorporating the sensor and platform variations. The sensor variations are caused by various subtle changes (imperfections) in the radar system circuitry (e.g., waveform generator, cables, etc.), and undesirable amplitude/phase fluctuations in the radiation pattern of the physical radar between the reference and test data collections; these are unknown and result in different 2D *Image Point Response* (IPR) or *Point Spread Function* (PSF) in the reference and test SAR images [14, ch. 8]. The platform (flight path) variations yield two sets of Doppler information that are not the same in the reference and test acquisitions. Thus, a dual-pass SAR change detection signal processor performs the following operations prior to pairing the reference and test SAR images [15]:

i. *Spatial registration* (also called *geo-registration*) of the reference SAR image with respect to the test SAR image using the available platform motion data (e.g., GPS, IMU, etc.);
ii. *Spectral registration* of both the test SAR image and the reference SAR image to extract the common Doppler data in the two images using the available platform motion data;
iii. *Blind calibration* of variations of the IPRs of the resultant (spatially and spectrally registered) reference and test SAR images using 2D adaptive filtering methods. This calibration also compensates for variations in the IPRs that are due to imperfect (errors in) motion data and require 2D auto-focusing to compensate for them (among other SAR system phase errors such as range-gate slip). These errors result in an image that is not the theoretical (ideal) SAR image.

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The success of the above-mentioned steps to detect changes in SAR images hinges upon another signal processing factor: the accuracy and consistency of the reconstruction algorithm that is used to form the SAR images. Error-free imaging algorithms such as wavefront or backprojection possess such properties (provided that they are correctly implemented). On the other hand, an approximation-based imaging method such as polar format processing (PFP) introduces *spatially-varying* errors (amplitude, phase, smearing, and shifting) that depend on the platform trajectory. Thus, unless the reference and test data acquisitions are obtained with *identica*l platform trajectories (and reconstruction scene center point), the user faces a formidable task to register and calibrate the two reference and test SAR images at all spatial points in the interrogated scene. (Identical platform trajectories for reference and test acquisitions cannot be achieved in practice.)

The Army Research Laboratory has been developing algorithms to combine spotlight mode SAR imagery from multiple looks at a scene. The different sub-apertures (from a flight past the scene) used to form the different looks help to ensure a certain degree of independence between the various images. Due to image pixel phase differences from one look to the next, however, we cannot coherently combine the different looks. Hence, we have opted for a non-coherent look-averaging scheme that heightens image contrast and reduces image speckle (i.e. pixel value variability) at the expense of a probable reduction in image resolution. This scheme still requires a tedious task of geo-registering spatially-warped images; yet, our multi-look SAR processor has been successful in improving the multi-look image contrast relative to that found in the single-look images. Using this procedure, we have been able to generate reference and test SAR images that are sufficiently well-registered for change detection purposes [6].

Furthermore, in certain wide-beamwidth stripmap SAR systems, the user may be faced with motion data that are not accurate enough for coherent integration of the acquired SAR data over a full aperture. In addition, auto-focusing of the resultant full aperture images would not be successful in most cases since the auto-focusing algorithm has to deal with relatively large radial motion errors. In these scenarios, non-coherent averaging of subaperture (multi-look) SAR imagery is considered to be a practical alternative since the dynamic range of the motion errors within each processed subaperture is not particularly large.

This paper addresses the problem of change detection in non-coherently averaged multi-look SAR imagery that is generated from relatively low-resolution images of a PFP or a SAR system with inaccurate platform motion data. Our approach is based on a 2D adaptive filtering method that has been used in [13]-[17] for change or moving target detection in SAR images that are formed using an error-free wavefront reconstruction algorithm. We call this method Signal Subspace Processing (SSP) and we refer to the resultant statistic that is used for change detection as the Signal Subspace Difference (SSD); these are briefly outlined in Section 2.

However, since the multi-look reference and test SAR imagery still contains some of the artifacts and errors of the PFP, we make modifications in the adaptive filtering method to make the change detection algorithm perform better—particularly in the imaging areas that are dominated by foliage or highly variable clutter phenomena. For this, we pose the change detection problem as a trinary hypothesis testing problem with individual hypotheses of: no change; incoming change; and outgoing change. An SSP-based approach is utilized to construct what we refer to backward and forward SSD signals (Section 3). The backward and forward SSD signals go through a normalization and a differencing operation; the resultant is a new statistic for the trinary hypothesis testing problem. At this juncture we note that the normalized backward and forward SSD signals can themselves be used in a binary hypothesis test to determine whether a target has either entered or exited the scene from one data collection time to the next. Ref. [18] provides a statistical analysis of the properties of the statistic used for just such a binary hypothesis test—designed to detect the addition of targets to the scene.

2. *CHANGE DETECTION VIA SIGNAL SUBSPACE PROCESSING*

Almost all sensory systems suffer from variations in IPR when they are used to interrogate the same scene or target. This is particularly true in SAR systems considering various electronic components that make up the hardware structure. There are also variations in IPR due to auto-focusing since no auto-focusing algorithm could be perfect. The simplest way to model these phenomena is via a spatially-invariant IPR. To show this, we let $f_1(x,y)$ represent the reference SAR image of a target scene, and $f_2(x,y)$ be the test SAR image of the same scene collected at another time point for change detection purposes.

First, we pose the problem as a *binary* hypothesis testing problem. Provided that the variations of the SAR sensor IPR are shift-invariant, under the null hypothesis H_0, that is, there is no change in the imaged scene, the test image can be related to the reference image via the following 2D convolution model [14, ch. 8]:

$$f_2(x,y) = \int_u \int_v h(u,v)\, f_1(x-u, y-v)\, du dv, \quad (1)$$

where the 2D filter $h(u,v)$ is spatially invariant across the entire image and represents the *unknown* miscalibrations in the radar system between the two data acquisitions. The above 2D continuous model can be converted into discrete form for the available reconstructed SAR imagery via

$$f_2(x_i, y_j) = \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} h_{mn} \; f_1(x_i - m\Delta_x, y_j - n\Delta_y), \quad (2)$$

where (Δ_x, Δ_y) represent the SAR image sample spacing in the (x, y) domain, and h_{mn} is an unknown impulse response (differential IPR) which depends on the variations of the SAR sensor in time. This model also accounts for subtle/small rotation and scaling of the test image relative to the reference image [13]. Notice that the unknown IPR is invariant in pixel location, that is, (x_i, y_j).

In imaging wide areas with a SAR system and/or a wide-beamwidth radar, the miscalibration filter is *spatially-varying*, implying that the filter coefficients, h_{mn}, are no longer spatially invariant across the entire image. In this case, a more general model that incorporates variations in both IPR and is a 2D spatially-varying system as shown in the following:

$$f_2(x, y) = \int_u \int_v \; h(u, v; x, y) \, f_1(u, v) \; du dv, \quad (3)$$

where $h(x, y; u, v)$, a function of both (x, y) and (u, v), and it represents the spatially-varying differential IPR that incorporates any spatial warping, variations in the SAR sensor, etc.. Here, (x, y) denote the test image (output) spatial coordinates and (u, v) denote the reference image (input) spatial coordinates. To develop a numerically-manageable solution for calibrating the test and reference images, we note that in practice the IPR can be approximated to be spatially-invariant in a small sub-region around a given pixel. Within the *k*-th sub-region, the discrete filter model for the above is

$$f_2^{(k)}(x_i, y_j) = \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} h_{mn}^{(k)} \quad f_1^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y). \quad (4)$$

This model states that each point in the test image is a linear combination of the reference image and its spatially shifted versions around that pixel point; the coefficients of the linear model, which identify the IPR for that pixel, are spatially varying. That is, we obtain a different set of coefficients for each of the *k* sub-regions. A numerical procedure to estimate the filter coefficients $h_{mn}^{(k)}$ from the reference and test SAR images, called *Signal Subspace Processing* (SSP), is outlined in [13], [14]. Briefly, the SSP is based on first identifying a linear signal subspace of the reference image and its shifted versions in the *k*-th sub-region:

$$\Phi_1^{(k)} = [\, f_1^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y); \; m = -n_x, \cdots, n_x \,, n = -n_y, \cdots, n_y \,]$$

.

Then with the help of , e.g., Gram-Schmidt orthogonalization procedure a set of orthonormal basis functions, $\Theta_1^{(k)}$ that span the signal subspace $\Phi_1^{(k)}$ is constructed, namely:

$$\Theta_1^{(k)} = [\theta_1^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y); \; m = -n_x, \cdots, n_x \,, n = -n_y, \cdots, n_y$$
$$x_i = x_{\min,k}, \; x_{\min,k}+1, \ldots, x_{\max,k},$$
$$y_j = y_{\min,k}, \; y_{\min,k}+1, \ldots, y_{\max,k}]$$

.

Finally, the test image in the *k*-th sub-region, that is, $f_2^{(k)}(x_i, y_j)$, is projected into these orthonormal basis functions to estimate the filter coefficients $h_{mn}^{(k)}$.

Under the second hypothesis H_1, that is, there is a change in the imaging scene, the test image cannot be related to the reference image via the model in (4). In this case, the SSP would result in a signal in the *k*-th sub-region denoted by

$$\hat{f}_2^{(k)}(x_i, y_j) = \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} h_{mn}^{(k)} \;\; \theta_1^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y), \quad (5)$$

that is not equal to the test image in the *k*-th sub-region, that is, $f_2^{(k)}(x_i, y_j)$. Here, $\hat{f}_2(x_i, y_i)$ denotes the estimate of $f_2(x_i, y_i)$ produced by the signal subspace processor (i.e. the projection of $f_2^{(k)}(x_i, y_j)$ onto the signal subspace , $\Theta^{(k)}$).

For change detection, we define the *Signal Subspace Difference* (SSD) signal via

$$f_{d12}^{(k)}(x_i, y_j) = f_2^{(k)}(x_i, y_j) - \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} h_{mn}^{(k)} \;\; \theta_1^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y) \quad (6)$$
$$= f_2^{(k)}(x_i, y_j) - \hat{f}_2^{(k)}(x_i, y_j)$$

Under the null hypothesis H_0, the SSD signal is (in theory) zero; however, under the hypothesis H_1, the SSD signal is not zero. Thus, the SSD can be used to detect change in the imaging scene. As we mentioned earlier, this method has been used on the SAR images that are formed via error-free wavefront reconstruction for coherent change detection [15] and moving target detection [16], [17].

3. *CHANGE DETECTION VIA NORMALIZED FORWARD-BACKWARD SIGNAL SUBSPACE PROCESSING*

As we mentioned earlier, the SSP method assumes a SAR signal processing and imaging that is error-free, and attempts to compensate for radar sensor variations. The driving force behind the work in this paper is to develop a SSP-based change detection statistic that is robust in dealing with not only radar sensor miscalibrations but also errors that are introduced in the image formation by the SAR system DSP. In what follows, the reference and test SAR images are averaged, multi-look PFP reconstructions.

3.1 *Forward-Backward SSP*

We pose the change detection in the averaged multi-look reference and test images as a trinary hypothesis testing problem. Under the null hypothesis H_0, we identify the *forward* SSP in the *k*-th sub-region to be the estimate of the test image via its projection into the signal subspace of the reference image [see Section II, eq. (5)]; that is,

$$\hat{f}_2^{(k)}(x_i, y_j) = \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} h_{mn}^{(k)} \quad f_1^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y)$$

The forward SSD is denoted as

$$f_{d12}^{(k)}(x_i, y_j) = f_2^{(k)}(x_i, y_j) - \hat{f}_2^{(k)}(x_i, y_j) \qquad (7)$$

Next, we identify the *backward* filter analogous to the forward filter in (3). That is, the spatially varying IPR that produces the reference image from the test image in the continuous spatial domain. We write the corresponding equation:

$$f_1(x, y) = \int_u \int_v g(x, y; u, v) f_2(u, v) \ dudv \qquad (8)$$

where $g(x, y; u, v)$ is the differential spatially-varying IPR. Within the *k*-th sub-region, the *backward* SSP is defined to be the estimate of the reference image via its projection into the signal subspace of the test image; that is,

$$\hat{f}_1^{(k)}(x_i, y_j) = \sum_{m=-n_x}^{n_x} \sum_{n=-n_y}^{n_y} g_{mn}^{(k)} \quad f_2^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y) \qquad (9)$$

where the linear signal subspace for the test image and its shifted versions in the *k*-th sub-region is identified via:

$$\Phi_2^{(k)} = [\, f_2^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y); \;\; m = -n_x, \cdots, n_x \,,\, n = -n_y, \cdots, n_y \,]$$

and also (after orthonormalization) by:

$$\Theta_2^{(k)} = [\theta_2^{(k)}(x_i - m\Delta_x, y_j - n\Delta_y); \;\; m = -n_x, \cdots, n_x \,,\, n = -n_y, \cdots, n_y$$
$$x_i = x_{\min,k}, \quad x_{\min,k} + 1, \ldots, x_{\max,k},$$
$$y_j = y_{\min,k}, \quad y_{\min,k} + 1, \ldots, y_{\max,k}\,].$$

The backward SSD is then constructed via

$$f_{d21}^{(k)}(x_i, y_j) = f_1^{(k)}(x_i, y_j) - \hat{f}_1^{(k)}(x_i, y_j) \qquad (10)$$

The error (change detection) signal at (x_i, y_j) is defined to be the difference of the *magnitude*s of the forward and backward SSD signals; that is,

$$e^{(k)}(x_i, y_j) = \left| \, f_{d12}^{(k)}(x_i, y_j) \right| - \left| \, f_{d21}^{(k)}(x_i, y_j) \right| \qquad (11)$$

We now examine this error signal under three hypotheses. From this point forward, we will concentrate on detecting the addition (or subtraction) of landmines to (or from) the region of interest, and we will use the terms "landmine" and "target" interchangeably.

i) Null Hypothesis H_0: Under the null hypothesis H_0, the error signal, in theory, is zero. To understand why this is so, we note that the manner the error signal is defined in (11) has a desirable utility in suppressing the miscalibration errors that are primarily due to the polar format processing. As we pointed out earlier, due to the PFP errors, a proper adaptation (projection) of $f_2^{(k)}(x_i, y_j)$ into the signal subspace $\Phi_1^{(k)}$ via SSP cannot be achieved under the null hypothesis H_0; that is, the forward SSD $f_{d12}^{(k)}(x_i, y_j)$ is not zero, and contains an undesirable *residual*. For the same reason, the backward SSP $f_{d21}^{(k)}(x_i, y_j)$ also contains some undesirable residuals. Our study indicates that the residuals in the forward and backward SSD signals have approximately the same shape and magnitude. Thus, the operation in eq. (11), that subtracts the *magnitudes* of the backward SSD from the *magnitude* of the forward SSD, suppresses (reduces) the effect of the undesirable residual errors in the SSD signals.

ii) Hypothesis H_1, Incoming Target (landmine): We identify the hypothesis H_1 as the scenario when there is no mine in the *k*-th sub-region of the reference image and $f_1^{(k)}(x_i, y_j)$ is the SAR signature of ground clutter; meanwhile, there is a mine in the *k*-th sub-region of the test image $f_2^{(k)}(x_i, y_j)$. Since $f_1^{(k)}(x_i, y_j)$ is ground clutter, the signal subspace $\Phi_1^{(k)}$ is composed of random noise-like orthonormal basis functions. Thus, the projection of $f_2^{(k)}(x_i, y_j)$ into $\Phi_1^{(k)}$ results in a forward SSP estimate $\hat{f}_2^{(k)}(x_i, y_j)$ that is noise-like. In this case, the forward SSD $f_{d12}^{(k)}(x_i, y_j)$ exhibits the presence of the mine.

Meanwhile, $f_2^{(k)}(x_i, y_j)$ contains a mine (a signal with structure); thus, the signal subspace $\Phi_2^{(k)}$ is dominated by the properties of a mine SAR signature. $f_1^{(k)}(x_i, y_j)$, that is a noise-looking signal, is likely to be orthogonal to the structured orthonormal basis functions of the signal subspace $\Phi_2^{(k)}$. Thus, the projection of $f_1^{(k)}(x_i, y_j)$ into $\Phi_2^{(k)}$ for the backward SSP, the outcome, $\hat{f}_1^{(k)}(x_i, y_j)$, is approximately a weak noise-looking signal. Hence, the backward SSP $f_{21d}^{(k)}(x_i, y_j)$ is also a weak noise-looking signal. Finally, the resultant error signal that is the difference of the forward and backward SSD [see eq. (11)] exhibits a *positive* component that indicates the *incoming (addition)* of a new target (mine) in the *k*-th sub-region.

iii) Hypothesis H_2, Outgoing Target (landmine): We identify the hypothesis H_2 as the scenario when there is a mine in the *k*-th sub-region of the reference image $f_1^{(k)}(x_i, y_j)$ clutter; however, the mine is removed in the *k*-th sub-region of the test image and $f_2^{(k)}(x_i, y_j)$. Using a similar analysis that we performed for the hypothesis H_1, one can show that the error signal of eq. (11) exhibits a *negative* component that indicates the *outgoing* target (mine) in the *k*-th sub-region.

3.2 *Normalized Forward-Backward SSP*

1. The Physical Problem and Motivation for Including Normalization: Researchers examining the change detection problem have also realized for some time that pixel value variability within a scene can wreak havoc on difference-based change detection algorithms [9], [10]. This implies that more false alarms should be expected from high-RCS areas of a radar image, since the variance of a clutter pixel value tends to increase with its intensity [2]. Hence, a higher mean clutter RCS level implies a larger clutter RCS variance, as we have observed in X-band SAR imagery collected at a depression angle of approximately 15^o. Based on these observations we could reasonably expect to encounter most change detection false alarms in a higher-RCS area, since the backscatter variance from this region is higher than that of the lower-RCS region. In such a case, the naturally occurring variations in RCS from image to image could approach the differences due to actual changes in the scene, especially if the change is due to the addition of a small target. We expect the lower RCS region we considered (a bare dirt background) to be benign at X-Band in the sense that targets placed on the bare dirt should have a better chance of being seen than targets placed, for example, in a high vegetation background [2]. Still, in spite of our optimism, we have noted that some sort of additional strategy is necessary to counteract the effects of variability within the high-RCS clutter regions.

The radar community has long recognized the need to normalize test statistics designed to detect the presence or absence of targets in a region under surveillance, e.g., [7]. Such a normalization step alleviates potential problems due to radar calibration differences from one data collection to the next, and it is commonly found in Constant False Alarm Rate (CFAR) detection algorithms [7], [8]. Statistical tests, such as size-α invariant tests [4], are another example of the same philosophy applied to the detection problem. In this section, we mimic a CFAR detection statistic and normalize our detection statistic (i.e. the error signal in eq. (11)) by the square root of the total power in the reference sub-region. This normalization produces a more robust statistic—reducing the number of false alarms due to highly variable clutter backgrounds. After describing the normalized statistic, we analyze its merits and, finally, we demonstrate these merits on a real change detection problem.

2. Definition of the Normalization Procedure: We denote the total energy of the reference image in the *k*-th sub-region via

$$E_1 = \sqrt{\sum_{(x_i,y_j)\in k-th} [\, f_1^{(k)}(x_i,y_j)]^2} \tag{12}$$

Consider the forward SSD signal that is normalized by this energy (its square root for proper units is used); that is,

$$\frac{f_{12d}^{(k)}(x_i,y_j)}{E_1} \tag{13}$$

Similarly, we define the total energy of the test image in the *k*-th sub-region via

$$E_2 = \sqrt{\sum_{(x_i,y_j)\in k-th} [\, f_2^{(k)}(x_i,y_j)]^2} \tag{14}$$

and the corresponding normalized backward SSD signal by

$$\frac{f_{21d}^{(k)}(x_i,y_j)}{E_2} \tag{15}$$

The normalized error signal is identified via the following:

$$e_{norm}{}^{(k)}(x_i,y_j) = \frac{|\, f_{12d}^{(k)}(x_i,y_j)\,|}{E_1} - \frac{|\, f_{21d}^{(k)}(x_i,y_j)\,|}{E_2} \tag{16}$$

Next, we examine this normalized error signal under the three hypotheses.

i) Null Hypothesis H_0: Under the null hypothesis H_0, the normalization of the strength of the SSD signal by the strength of the *k*-th sub-region should reduce the strength of the undesirable residual errors. For instance, suppose there exists a strong reflector (e.g., a trihedral) in the *k*-th sub-region in both the reference and test images. The undesirable residual errors of this target in both the backward and forward SSD signals is comparable or, at times, larger than the signature of a mine, e.g., 20 dB below the SAR signature of a trihedral. However, the relative strength of the trihedral residual errors in the SSD signals would be reduced with the normalization operation.

ii) Hypothesis H_1, Incoming Target: As we mentioned earlier, in this hypothesis, there is no mine in the *k*-th sub-region of the reference image $f_1^{(k)}(x_i,y_j)$, but there is a mine in the *k*-th sub-region of the test image $f_2^{(k)}(x_i,y_j)$; in this case, we showed that, the forward SSD $f_{d12}^{(k)}(x_i,y_j)$ exhibits the presence of the mine. Since the reference image $f_1^{(k)}(x_i,y_j)$ corresponds to ground clutter, its energy E_1 is relatively low. Thus, the normalization of forward SSD $f_{d12}^{(k)}(x_i,y_j)$ with E_1 results in increase in the relative strength of the mine signature.

We also noted that the backward SSP $f_{d21}^{(k)}(x_i,y_j)$ is a weak noise-like signal under H_1. Since the test image $f_2^{(k)}(x_i,y_j)$ contains a mine, its energy E_2 is relatively high. Thus, the normalized backward SSP

$f_{d21}^{(k)}(x_i, y_j)$ is further weakened after normalization with E_2.

Based on these observations regarding the normalized SSD signals under H_1, one can conclude that the resultant normalized error signal in (16) should be more robust in exhibiting a *positive* signature that is indicative of an *incoming* target in the *k*-th sub-region than the error signal in (11).

iii) Hypothesis H_2, Outgoing Target: Using an analysis similar to the one for the hypothesis H_1, we can conclude that the error signal of eq. (16) exhibits a more prominent *negative* component that indicates the *outgoing* target in the *k*-th sub-region than the error signal in (11).

5. *CONCLUSION*

This paper outlined a method for change detection in non-coherently averaged multi-look SAR imagery. The application of a 2D adaptive filtering method, also known as signal subspace processing, using a normalized signal subspace difference signal was demonstrated to yield an effective approach to not only compensate for calibration errors between reference and test SAR imagery but also reconstruction errors that are due to using an approximation-based imaging algorithm (e.g., PFP) or significant unknown motion errors along a long synthetic aperture.

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