An improved neighborhood-based ratio approach for change detection in SAR images

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ABSTRACT
The speckle noise of synthetic aperture radar (SAR) images limits its application in change detection. Compared with improved ratio (IR) and log-ratio (LR) operators, the neighborhood-based ratio (NR) technique can restrain the influence of speckle noise and is more suitable for change detection in SAR images. However, we find three drawbacks of NR by analyzing this method carefully. To overcome these defects, we propose an improved neighborhood-based ratio (INR) approach for change detection in SAR images. INR restructure the NR operator to exploit the neighborhood information more reasonably and is expected to reduce the impact of speckle noise better. IR, LR, mean ratio operator, NR, and INR are tested on two data sets to compare their performances in change detection of SAR images. Experimental results show that the proposed method can obtain better difference image than other state-of-art methods and improve the accuracy of change detection in SAR images effectively.

KEYWORDS
Change detection; neighborhood information; ratio operator; synthetic aperture radar (SAR); receiver operating characteristic (ROC)

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Introduction
Change detection is a technique to detect the land cover changes that have occurred in the investigated area by using remote sensing images acquired in the same geographical area at two different dates (Bruzzone & Prieto, 2000). In recent years, this technique has been widely used in environmental monitoring (Onur, Makav, Sari, & Sönmez, 2009), urban studies (Ye & Chen, 2015), forest monitoring (Chehata, Orny, Boukir, Guyon, & Wigneron, 2014), agricultural surveys (Li & Narayanan, 2003), disaster assessment (D’Addabbo et al., 2016), etc.

The optical remote sensing images have been widely used in change detection (Bovolo, Marchesi, & Bruzzone, 2012; Lorenzo & Diego Fernández, 2002; Neagoe, Stoica, Ciurea, Bruzzone, & Bovolo, 2014; Zhuang, Deng, Fan, & Yu, 2016) due to its advantages such as a large number of optical remote sensing satellites, abundant spectral information, etc. However, the optical remote sensing satellites are sensitive to atmospheric and sunlight conditions, for example, they cannot acquire effective ground natural scene information at night. Compared with optical satellites, synthetic aperture radar (SAR) can penetrate clouds, fog, and haze to obtain the images, and is insensitive to sun-illumination conditions. For instance, under harsh environments such as heavy rain, floods, and earthquakes, the optical satellites are hard to obtain the high-quality images because of the insufficient light and clouds, but the important real-time images can be acquired by SAR. Since the 1950s, SAR has been widely used in ground subsidence monitoring (Fan, Gao, Yang, Deng, & Yu, 2015), topographic mapping (Mason et al., 2016), resource exploration (Hasager, Badger, Peña, Larsén, & Bingöl, 2011), environment remote sensing (Satyabala, 2016), and military (Hu, Tian, Dai, & Wang, 2011), etc. In recent years, with the rapid development of SAR technology, change detection has become one of the most interesting topics in information extraction of SAR images (Akbari et al., 2016; Hachicha & Chaabane, 2014; Lu et al., 2015; Marin, Bovolo, & Bruzzone, 2015).

Generating the difference image is a key step for change detection in SAR images. In this context, researchers first used subtraction operator or ratio (R) operator to acquire the difference image. Compared with subtraction operator, R operator can decrease the influence of calibration and radiometric errors, and is suitable for obtaining the difference image from SAR images (Rignot & Van Zyl, 1993; Singh, 1989). However, in the difference image acquired with R operator, the changes with different radiometrics (e.g., with increasing and decreasing radiometrics) cannot be distinguished with any single threshold algorithm. An improved ratio (IR) operator was proposed to solve this problem masterly (Oliver & Quegan, 2004). For multi-temporal pixel pair, IR uses the smaller intensity as numerator and the larger intensity as denominator. Considering the noise of SAR
images is multiplicative speckle noise (Argenti & Alparone, 2002; Touzi, 2002), logarithmic transformation can not only transform multiplicative noise into additive noise but also compress the value range of R operator. Log–ratio (LR) operator was widely used in change detection of SAR images (Bovolo & Bruzzone, 2005; Bovolo, Marin, & Bruzzone, 2013; Celik, 2010). Although LR can reduce the influence of speckle noise to a certain extent, it ignores the neighborhood information of SAR images. On the basis of IR, mean ratio (MR) operator, employing the local mean information of SAR images to restrain the impact of speckle noise, was reported for change detection in SAR images (Ma, Gong, & Zhou, 2012). However, MR presents a poor performance in heterogeneity area such as edge area because it does not consider the similarity of the local pixels. Hence, the neighborhood-based ratio (NR) method for change detection in SAR images (Gong, Cao, & Wu, 2012). This method employs heterogeneity of the local area, widely used in auto-adaptive filter algorithms (Argenti & Alparone, 2002; Lopes, Touzi, & Nezry, 1990), to control the influence weight of the neighborhood information to the center pixel. The authors have proved that the difference image acquired by NR was better than IR and LR, but they did not compare the performances of NR and MR. The heterogeneity of the local area can restrain speckle noise and preserve the detail information so it is expected that the difference image obtained by NR is better than MR. However, experimental results show that the performance of NR is poor than MR in change detection of SAR images. We are very puzzled about this result and try to find the reasons. Thus, we find three drawbacks of NR by analyzing it carefully. First, only a heterogeneity measurement is computed by NR in the same position of multi-temporal SAR images. Second, heterogeneity measurement is the weight to balance between restraining speckle noise and preserving the detail information, thus, its expected dynamic range is [0, 1]. However, the heterogeneity measurement is greater than 1 while the standard deviation of the neighborhood area is greater than its mean. Third, in the difference image acquired with NR, the changed pixel should have smaller intensity and the unchanged pixel should have larger intensity. We would correct it by referring to IR and MR. Therefore, we propose an improved neighborhood-based ratio (INR) method for change detection in SAR images. Besides, we add a constant C to INR operator to avoid numerical instability of ratio operation.

This paper is organized into five sections. Section 2 deals with INR and the relevant methods. Section 3 presents the data sets used in this paper and the analysis of receiver operating characteristic (ROC) curves of the difference images. The change maps obtained with different methods are compared in Section 4. Finally, conclusions are drawn in Section 5. The general scheme of the proposed approach is shown in Figure 1.

Related works and the proposed approach

This section introduces the distribution of the speckle noise of SAR intensity image firstly. Then IR, LR, MR, and NR are reported. Finally, the proposed method is described in detail.

The presence of speckle noise influences the application of SAR images (Argenti & Alparone, 2002; Touzi, 2002). The probability density distribution of multilook SAR intensity image can be assumed as Gamma distribution (Rignot & Van Zyl, 1993)

\[ p(I_0/\langle I_0 \rangle) = \frac{N^N I_0^{N-1}}{\langle I_0 \rangle^N (N-1)!} \exp \left\{ -\frac{NI_0}{\langle I_0 \rangle} \right\} \]  

(1)

where \( \langle I_0 \rangle \) is the mean intensity of a homogeneous region, \( N \) represents the equivalent number of looks (ENL) of the SAR image. \( N \) is used to measure the level of speckle noise, the SAR image with serious speckle noise has a smaller \( N \) (Cui, Zhou, Yang, & Yamaguchi, 2011).

Related works

Let us consider two SAR images \( I_1 \) and \( I_2 \) obtained on the same geographical area at two dates. Let \( I_1(x) \) represent the gray value of the pixel at position \( x \) on image \( I_1 \), \( I_2(x) \) is the gray value of the pixel at position \( x \) on image \( I_2 \). Then, R operator is shown as Equation (2) (Singh, 1989)

\[ DR(x) = \frac{I_1(x)}{I_2(x)} \]  

(2)
where $\text{DR}$ is the difference image generated by R, $\text{DR}(x)$ is the gray value of the pixel at position $x$ on image DR. Rignot and Van Zyl (1993) have confirmed that R is more robust to calibration and radiometric errors than subtraction operator (Rignot & Van Zyl, 1993) so that the difference image acquired by R is better than that acquired by subtraction operator.

On the basis of Equation (1), the distribution of $\text{DR}$ is derived as the following equation (Rignot & Van Zyl, 1993)

$$p\left(r/\{I_1\}, \{I_2\}\right) = \frac{(2N-1)!\tilde{r} r^{N-1}}{(N-1)!\left(\tilde{r} + r\right)^N}$$

(3)

where $r = I_1/I_2$, $\tilde{r} = \langle I_1\rangle / \langle I_2\rangle$, $\{I_1\}$ and $\{I_2\}$ represent the mean intensities of a homogeneous region in images $I_1$ and $I_2$, respectively. $\tilde{r}$ plays an important role in the distribution shown in Equation (3). Rignot and Van Zyl (1993) summarized that using mean intensity can reduce the negative effect of speckle noise on change detection in SAR images, which is also the motivation of reporting NR in the literature (Gong et al., 2012).

Changes occurred in multi-temporal SAR images can be divided into two types: 1) $I_1(x)$ is smaller than $I_2(x)$; 2) $I_1(x)$ is larger than $I_2(x)$. For the former, $\text{DR}(x)$ computed by Equation (2) is smaller than 1, but $\text{DR}(x)$ is larger than 1 in the second situation. Thus, a dual-threshold algorithm is necessary to yield the change map from $\text{DR}$, which increases the difficulty of change detection. In order to generate the change map with a single threshold algorithm, it is necessary to merge the above two change types as one. IR addressed this issue and was widely used for change detection of SAR images. It is presented in Equation (4) (Oliver & Quegan, 2004)

$$\text{DIR}(x) = 1 - \frac{\min\{I_1(x), I_2(x)\}}{\max\{I_1(x), I_2(x)\}}$$

(4)

where $\text{DIR}$ is the difference image generated by IR, $\text{DIR}(x)$ is the gray value of the pixel at position $x$ on image DIR. In DIR, the changed pixel has larger intensity while the unchanged pixel has smaller intensity. Thus, it is simple to generate the change map from DIR by employing a single threshold algorithm.

As mentioned in Section 1, LR can transform multiplicative noise into additive noise and can compress the value range of the difference image. LR operator is given as Equation (5) (Bovolo & Bruzzone, 2005)

$$\text{DLR}(x) = \ln(I_1(x)/I_2(x))$$

(5)

where $\text{DLR}$ is the difference image generated by LR, $\text{DLR}(x)$ is the gray value of the pixel at position $x$ on image DLR.

MR, different from R, IR, and LR, employs the mean of the local area to reduce the negative influence of speckle noise on change detection of SAR images. The difference image DMR generated with MR can be calculated by Equation (6)

$$\text{DMR}(x) = 1 - \frac{\min\{u_1(x), u_2(x)\}}{\max\{u_1(x), u_2(x)\}}$$

(6)

where $\text{DMR}(x)$ is the gray value of the pixel at position $x$ on image DMR, $u_1(x)$ is the mean of the local area at position $x$ on image $I_2$. Similar to IR, the change map of MR is yielded by using a single threshold algorithm.

NR

NR utilizes heterogeneity measurement $\partial$ to combine the center pixel information and its neighborhood information (Gong et al., 2012). $\partial$ can well balance between restraining speckle noise and preserving the detail information. Although IR is insensitive to calibration and radiometric errors, it is still affected by the residual multiplicative noise. However, NR is robust to calibration and radiometric errors, and residual multiplicative noise.

Let $\Omega_x$ represent the neighborhood of two SAR images at position $x$. NR operator is shown as Equation (7) (Gong et al., 2012)

$$\text{DNR}(x) = \partial \times \frac{\min\{I_1(x), I_2(x)\}}{\max\{I_1(x), I_2(x)\}} + (1 - \partial) \sum_{i \in \Omega_x} \frac{\min\{I_1(i), I_2(i)\}}{\max\{I_1(i), I_2(i)\}}$$

(7)

where $\text{DNR}$ is the difference image generated by NR, $\text{DNR}(x)$ is the gray value of the pixel at position $x$ on image DNR. The larger $\text{DNR}(x)$, the higher similarity between multi-temporal SAR images, so the corresponding pixel has a greater probability to be unchanged. $\partial = \sigma(x)/\mu(x)$ represents the heterogeneity measurement of $\Omega_x$, high values correspond to heterogeneous areas while low values refer to homogeneous areas. $\sigma(x)$ is the standard deviation of $\Omega_x$, $\mu(x)$ is the mean of $\Omega_x$. For heterogeneous areas, the first part of Equation (7) plays an important role in generating the difference image. For homogeneous areas, the second part of Equation (7) plays a lead role in generating the difference image. The size of $\Omega_x$ is relevant to ENL of SAR images (Cui et al., 2011; Gong et al., 2012). SAR image with larger ENL should use a smaller size because its speckle noise is slight.

The proposed approach

Three drawbacks of NR have been introduced in Section 1, the following part will present INR with detailed description of them. The analysis process on how to improve NR is presented in the appendix.
The form of classic R operator is shown as Equation (2). We restructure the Equation (7) into Equation (8) with the similar form of Equation (2).

\[
DNR(x) = \frac{\partial_{\text{min}} \text{SN}_{\text{max}} + (1 - \partial) \text{SN}_{\text{min}}}{\text{SN}_{\text{max}}}
\]

where \(\partial_{\text{min}} = \min\{I_1(x), I_2(x)\}\), \(\partial_{\text{max}} = \max\{I_1(x), I_2(x)\}\), \(\text{SN}_{\text{min}} = \sum_{i: \Omega^x \ni x} \min\{I_1(i), I_2(i)\}\), \(\text{SN}_{\text{max}} = \sum_{i: \Omega^x \ni x} \max\{I_1(i), I_2(i)\}\).

Obviously, Equation (8) is different from Equation (2). If we improve NR operator referring to Equation (2), it is expected to get a better difference image.

At position \(x\), the number of neighborhood areas is the same as the number of the multi-temporal SAR images. However, only a heterogeneity measurement is calculated in Equation (7) which combines multi-temporal neighborhood areas into a bigger neighborhood area. Let \(\partial_1\) represent the heterogeneity measurement of the neighborhood area \(\Omega^x \ni x\) at position \(x\) on the SAR image acquired in time \(T_1\). Let \(\partial_2\) represent the heterogeneity measurement of the neighborhood area \(\Omega^x \ni x\) on the SAR image acquired in time \(T_2\). For the unchanged areas between multi-temporal SAR images, \(\partial \approx \partial_1 \approx \partial_2\), because multi-temporal neighborhood areas include similar information. However, for the changed areas between multi-temporal SAR images, there is a bigger difference between multi-temporal neighborhood areas. For instance, the following situation may occur: \(\partial_1\) and \(\partial_2\) both have smaller values, that is, the multi-temporal neighborhood areas are homogeneous areas, whereas \(\partial\) has a larger which indicates the neighborhood area is a heterogeneous area. NR is designed for change detection of SAR images, the neighborhood information of changed area plays an important role in restraining the speckle noise and identifying the changed pixel, which should be fully and reasonably used to change detection.

Equation (9), with the form of Equation (2), makes full use of multi-temporal neighborhood areas.

\[
DINR'(x) = \frac{\min\{((\partial_1 I_1(x) + (1 - \partial_1) \times u'_1), (\partial_2 I_2(x) + (1 - \partial_2) \times u'_2)\}}{\max\{((\partial_1 I_1(x) + (1 - \partial_1) \times u'_1), (\partial_2 I_2(x) + (1 - \partial_2) \times u'_2)\}}
\]

where \(DINR'\) is the difference image generated by Equation (9), \(DINR(x)\) is the gray value of the pixel at position \(x\) on image \(DINR', u'_1\) is the mean of \(\Omega^x\) which has removed the center pixel, \(u'_2\) is the mean of \(\Omega^x\) which has removed the center pixel. The larger \(DINR'(x)\), the higher similarity between multi-temporal SAR images, so the corresponding pixel has a greater probability to be unchanged.

The desired dynamic range of \(\partial\) is [0, 1] because it is used as a weight to balance between restraining speckle noise and preserving the details of SAR image. However, \(\partial\) is greater than 1 while the standard deviation of the neighborhood area is greater than its mean, which leads to \((1 - \partial) < 0\). In this situation, \(DNR(x)\) may be less than 0, which is apparently unreasonable because both \(I_1(x)\) and \(I_2(x)\) are bigger than 0 and the difference values obtained by IR, LR, and MR are bigger than 0. Therefore, it is necessary to adjust the value range of \(\partial\) to [0, 1] if \(\partial\) is used as a weight. In other words, it is inappropriate to directly use \(\partial\) as a weight to balance between restraining speckle noise and preserving the detail information because \(\partial\) is larger than the ideal adjustment weight. After adjusting the value range of \(\partial\) to [0, 1], the large new value still indicates a more heterogeneous area and is reasonable to be used as a weight for balancing between restraining speckle noise and preserving the detail information. To make the same \(\partial\) before normalization are still equal to each other after normalization in multitemporal SAR images, it is necessary to use the same normalization parameter for multitemporal images. Therefore, we normalize the heterogeneity measurement of multi-temporal SAR images with Equation (10).

\[
\begin{align*}
\partial_n1 &= \frac{\partial_1}{\partial_{\text{max}}}, \\
\partial_n2 &= \frac{\partial_2}{\partial_{\text{max}}}
\end{align*}
\]

where \(\partial_n1\) and \(\partial_n2\) are normalized heterogeneity measurements, \(\partial_{\text{max}}\) is the maximum value of all the heterogeneity measurements of multi-temporal SAR images. There is small difference in the maximum values of \(\partial\) in multitemporal SAR images because they were acquired in the same geographical area.

In order to let the changed pixel of difference image have a larger intensity so that the changed areas present well visual performance (such as Figure 10). Referring to Equations (4) and (6), and using Equation (10) to normalize heterogeneity measurement, we develop Equation (9) into Equation (11)

\[
DINR(x) = 1 - \frac{\min\{((\partial_n1 I_1(x) + (1 - \partial_n1) \times u'_1), (\partial_n2 I_2(x) + (1 - \partial_n2) \times u'_2))\}}{\max\{((\partial_n1 I_1(x) + (1 - \partial_n1) \times u'_1), (\partial_n2 I_2(x) + (1 - \partial_n2) \times u'_2))\}}
\]
where $DINR$ is the difference image generated by INR, $DINR(x)$ is the gray value of the pixel at position $x$ on image $DINR$.

The second part of Equation (11) is numerical instability while denominator is close to zero. To overcome this drawback, we add a constant $C$ to Equation (11) and get Equation (12) which is the final form of INR operator

$$DINR(x) = 1 - \frac{\min\{(\partial_{n1}I_1(x) + (1 - \partial_{n1}) \times u'_1) \times u'_1, (\partial_{n2}I_2(x) + (1 - \partial_{n2}) \times u'_2) \times u'_2\} + C}{\max\{(\partial_{n1}I_1(x) + (1 - \partial_{n1}) \times u'_1) \times u'_1, (\partial_{n2}I_2(x) + (1 - \partial_{n2}) \times u'_2) \times u'_2\} + C}$$

(12)

where the constant $C$ is calculated with Equation (13) (Wang, Bovik, Sheikh, & Simoncelli, 2004)

$$C = (kL)^2$$

(13)

where $L$ is the dynamic range of the pixel values ($L = 255$ for 8-bit grayscale images), $k \ll 1$ is a small constant.

Analysis of ROC curves of the difference images

ROC curve (Ulehla & Martin, 1971) originated from statistical decision theory for explaining the relationship of classification between the hit rate and the false alarm rate. In the Second World War, it was used to evaluate the observation capability of radar. Then, it was widely used in clinical medicine (Zweig & Campbell, 1993), radiology (Obuchowski, 2003), risk prediction (Cook, 2007), ecology (Peterson, Papeş, & Soberón, 2008), machine learning (Spackman, 1989), etc. It is intuitive to compare the performances of different classifiers if their ROC curves are plotted on the same coordinate system (Webb & Ting, 2005). Change detection can be seen as a binary classification problem in which a pixel is divided into changed or unchanged type. IR, LR, MR, NR, and INR can be seen as the special binary classifiers designed for change detection. Therefore, ROC curve is employed to qualitatively analyze the difference images generated with different methods on two data sets.

ROC curves are first used to analyze the optimal neighborhood size of MR, NR, and INR because the difference images acquired with them are relevant to the size of neighborhood area. We used the neighborhood sizes $3 \times 3 \sim 11 \times 11$ on two data sets in the initial experiments. The experimental results with neighborhood sizes $3 \times 3 \sim 9 \times 9$ were presented in this paper because the max neighborhood size of the best neighborhood size of different methods on two data sets is $7 \times 7$.

Experimental data sets

The first data set is composed of two images (i.e., Figure 2(a,b)) acquired during and after the rainy season in the same area through ALOS-1. The area shown in the two images is a section (400 \times 400 pixels with resolution 10 m) of a scene acquired in Peixian, China, in July 2008 and August 2009. A part of the Dasha River is included in the data set, the main classes of the data set are water bodies, farmland and buildings. Figure 2(c), the reference map of the two images used to facilitate a quantitative evaluation of the change maps, is defined manually according to an accurate and time-consuming visual inspection of the considered SAR images.

The second data set (i.e., Figure 3(a,b)) used in this study represents a section (301 \times 301 pixels with resolution 30 m) of two images acquired by ERS-2 over an area in Bern, Switzerland, in April 1999 and May 1999. The main classes of the image acquired in April 1999 are farmland and buildings while the main classes of the image acquired in May 1999 are water bodies, farmland and buildings. The changes are

Figure 2. Multi-temporal images in Peixian. (a) Image acquired in July, 2008. (b) Image acquired in August, 2009. (c) Map of changed areas (ground truth) used as reference in the experiments.
caused by flooding. Figure 3(c), defined as Figure 2(c), is the reference map used to facilitate a quantitative evaluation of the change maps.

**Difference images related to Peixian data set**

Figure 4 shows the difference images generated from Peixian data set by using MR. Their ROC curves are presented in Figure 5. The ROC curve of the better difference image is closer to the upper left corner. The performance of the difference image acquired with the neighbourhood size $3 \times 3$ is the worst. The difference image is better with the neighborhood size increasing from $3 \times 3$ to $7 \times 7$. The difference image acquired with the neighborhood size $9 \times 9$ is slightly worse than that acquired with the neighborhood size $7 \times 7$. Thus, the difference image acquired with the neighborhood size $7 \times 7$ performs best.

Figure 6 shows the difference images obtained from Peixian data set by using NR. The difference image, acquired with the neighborhood size $7 \times 7$,
performs best in view of the ROC curves shown in Figure 7. The difference image acquired with the neighbourhood size 3 × 3 performs worst because of the influence of speckle noise.

The difference images, obtained from Peixian data set with INR, are presented in Figure 8. The ROC curves of the difference images shown in Figure 8 are given in Figure 9. The best difference image is that acquired with the neighborhood size 7 × 7 and the worst difference image is that obtained with the neighborhood size 3 × 3.

The difference images, obtained from Peixian data set with IR and LR, are shown in Figure 10. From the above analysis, we know that the best difference images of MR, NR and INR are Figures 4(c), 6(c), and 8(c), respectively. Their ROC curves are presented in Figure 11. The worst difference image is that acquired with IR, whose ROC curve is closer to the lower right corner. The difference image generated with LR is better than IR because LR can transform multiplicative noise into additive noise. The performances of MR, NR, and INR are better than IR and LR because they employ the
neighborhood information to reduce the negative impact of speckle noise. The difference image acquired with the proposed approach performs best because INR reasonably exploits heterogeneity measurement to balance between restraining speckle noise and preserving the details of SAR image.

**Difference images related to Bern data set**

Figure 12 shows the difference images acquired from Bern data set by using MR. Their ROC curves are presented in Figure 13. The ROC curves related to

![Figure 9. ROC curves of the difference images shown in Figure 8.](image)

![Figure 10. Difference images generated from Peixian data set by using (a) IR and (b) LR.](image)

![Figure 11. ROC curves of the difference images acquired from Peixian data set with different methods.](image)
Peixian data set are smooth, thus it is easy to compare their performances. However, there are a lot of cross-points among the ROC curves related to Bern data set. For example, $P$ is a cross-point of the ROC curves corresponding to the difference images acquired with the neighborhood sizes $3 \times 3$ and $9 \times 9$. In the left of $P$, the ROC curve corresponding to the neighborhood size $9 \times 9$ is on top of that corresponding to the neighborhood size $3 \times 3$. Whereas the opposite situation occurred in the right of $P$. It is hard to compare the ROC curves according to the aforementioned principle that the performance of the classifier is better while the ROC curve is closer to the upper left corner. In this situation, the right part of $P$ should be used to compare their performances (Ulehla & Martin, 1971). Thus the difference image acquired with the neighborhood size $3 \times 3$ is better than that with the neighborhood size $9 \times 9$, and it is also the best difference image acquired with MR.

Figure 14 presents the difference images generated from Bern data set by using NR. The difference image, acquired with the neighborhood size $3 \times 3$, performs worst in view of the ROC curves shown in Figure 15. There are many cross-points among the
difference images acquired with the neighborhood sizes $5 \times 5$, $7 \times 7$, and $9 \times 9$. By comparing the ROC curves in the right part of cross-points, we can know that the difference image acquired with the neighborhood size $5 \times 5$ is slightly better than that acquired with the neighborhood sizes $7 \times 7$ and $9 \times 9$.

Figure 16 presents the difference images acquired from Bern data set with INR. Their ROC curves are shown in Figure 17. By comparing the ROC curves in the right part of cross-points, we can know that the best difference image is that acquired with the neighborhood size $5 \times 5$ and the worst difference image is that obtained with the neighborhood size $9 \times 9$.

Figure 18 presents the difference images obtained from Bern data set by utilizing IR and LR. From the above analysis, we know that the best difference images of MR, NR, and INR are Figures 12(a), 14(b), and 16(b), respectively. The ROC curves presented in Figure 19 correspond to the difference images shown in Figures 18, 12(a), 14(b) and 16(b). The difference image generated with LR is better than IR because LR can transform multiplicative noise into additive noise. IR and LR perform worse than MR, NR, and INR because they neglect the neighborhood information of SAR images. The difference image acquired with INR, whose ROC curve is closer to the upper left corner, performs best because INR reasonably exploits the neighborhood information of SAR images.

**Analysis of change maps**

To further confirm the effectiveness of the proposed approach, we quantitatively analyze the change maps by using missed alarms, overall error, and detected changes which are also used in other literature (Bazi, Bruzzone, & Melgani, 2005; Bruzzone & Prieto, 2000; Zhuang et al., 2016). The change maps related to MR, NR, and INR are yielded with the best difference images determined with ROC curves.

Confirming a reasonable threshold is the critical issue to yield the change map. Existing automatic threshold selection methods can be divided into three categories: nonparametric automatic threshold selection methods (Kapur, Sahoo, & Wong, 1985; Milligan & Cooper, 1985; Otsu, 1979; Wong & Sahoo, 1989), semi-parametric automatic threshold selection method.
and automatic threshold selection methods based on prior knowledge (Bazi et al., 2005; Bruzzone & Prieto, 2000; Kittler & Illingworth, 1986). However, each of the aforementioned threshold selection methods has its own applicability and limitations. This is because they calculate the optimal threshold under a certain assumption, and this threshold is unreasonable when the assumption is inappropriate (Bruzzone & Prieto, 2000). In order to avoid the negative impact of the unreasonable threshold on the experiments, manual trial-and-error procedure (MTEP), widely used in the literature focusing on

![Figure 17. ROC curves of the difference images shown in Figure 16.](image)

![Figure 18. Difference images generated from Bern data set by using (a) IR and (b) LR.](image)

![Figure 19. ROC curves of the difference images obtained from Bern data set with different methods.](image)
change detection (Bovolo & Bruzzone, 2005; Bovolo et al., 2012; Lorenzo & Diego Fernández, 2002; Lu et al., 2015), is employed to obtain the threshold.

**Change maps related to Peixian data set**

Figure 20 presents the change maps obtained from Peixian data set with different methods. Part of the water bodies of the Dasha River becomes land after the rainy season, thus the changes represent the contraction of water bodies of the Dasha River. Compared with Figure 2(c), Figure 20(a,b) have many missed pixels in changed area and have many discrete white speckle noise in unchanged area. Figure 20(c-e) have less discrete white speckle noise and have more changed pixels because they utilize the neighborhood information of SAR images to yield the difference images.

Table 1 presents the missed alarms, overall error, and detected changes of the change maps shown in Figure 20. A better change map characterizes the smaller missed alarms and overall error and more detected changes.

The analysis of Table 1 is as follows: 1) the change map acquired with IR possesses the maximum missed alarms (3635) and overall error (4134) and the minimum detected changes (2586); 2) the change map generated with LR is better than IR because the former can transform multiplicative noise into additive noise; 3) MR, NR and INR outperform IR and LR from the perspective of missed alarms, overall error, and detected changes because of the use of neighborhood information; 4) MR performs better than NR because NR utilizes the neighborhood information unreasonably; and 5) the change map generated with INR has the minimum missed alarms (1047) and overall error (1302), and has the maximum detected changes (5174), because the proposed approach can reasonably exploit the neighborhood information of SAR images so that it can well balance between robustness of speckle noise and preserving the details of SAR image.

**Change maps related to Bern data set**

Figure 21 presents the change maps generated from Bern data set with different methods. Part of the farmland becomes water bodies which is caused by flooding, thus the changes represent the appearance of a new class water bodies. Similar to the change maps acquired from Peixian data set, the change maps obtained with IR and LR have many discrete white speckle noise in unchanged area. The change maps generated with MR, NR, and INR are in good agreement with Figure 3(c) because they use the neighborhood information of SAR images.

The missed alarms, overall error, and detected changes of the change maps related to Bern data set
are given in Table 2. Considering all the three measurements, the change map acquired with IR is the worst while the best one is generated with INR. Compared with the change map obtained by using IR, the change map yielded by using LR has fewer missed alarms and overall error and has more detected changes. This is because LR can transform multiplicative noise into additive noise. MR, NR, and INR perform better than IR and LR because the latter neglect the neighborhood information of SAR images. The change map acquired with NR is worse than MR, because NR exploits the neighborhood information unreasonably which has been analyzed in Section 2. INR outperforms MR because it reasonably uses the neighborhood information by heterogeneity measurement.

Conclusions

An improved approach for change detection in multi-temporal SAR images is proposed in this paper. This method confirms the influence weight of the neighborhood information to the center pixel by heterogeneity measurement. It is reasonable in theory and has the similar form with IR and MR. When the denominator is close to zero, the numerical stability of INR is guaranteed by employing a constant $C$. The experiments are conducted on two data sets to confirm the performance of INR. Both ROC curves of the difference images and missed alarms, overall error, and detected changes of the change maps validate that INR is more insensitive to speckle noise and is more suitable for change detection in SAR images. This work contributes to 1) develop a novel approach INR by solving three drawbacks of NR; and 2) guarantee the numerical stability of INR by employing a constant.

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Disclosure statement

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**Appendix**

This section would present the analysis process on how to improve NR.

When we want to exploit the multi-temporal neighborhood information and improve the Equation (7) referring to the Equation (2), we first consider the INR shown as Equation (14)

\[
\text{DINR}^{\mu}(x) = \frac{\partial_1 \times \min\{I_1(x), I_2(x)\} + (1 - \partial_1) \times u_1^{\mu}}{\partial_2 \times \max\{I_1(x), I_2(x)\} + (1 - \partial_2) \times u_2^{\mu}}
\]  

(14)

where \(u_1^{\mu} = \frac{1}{N' - 1} \sum_{i \notin \Omega_{i}, \Omega_{x}} \min\{I_1(i), I_2(i)\}\), \(u_2^{\mu} = \frac{1}{N' - 1} \sum_{i \notin \Omega_{i}, \Omega_{x}} \max\{I_1(i), I_2(i)\}\), \(N'\) is the number of the pixels in the neighborhood area.

Equation (14) seems to be reasonable. However, Equation (14) can be restructured into Equation (15) while \(I_1(x) < I_2(x)\)

\[
\text{DINR}^{\mu}(x) = \frac{\partial_1 \times I_2(x) + (1 - \partial_1) \times u_1^{\mu}}{\partial_2 \times I_1(x) + (1 - \partial_2) \times u_2^{\mu}}
\]  

(15)

where \(\partial_1 \times I_2(x)\) is obviously unreasonable because \(\partial_1\) is the heterogeneity measurement of the neighborhood area acquired in time \(T_1\) while \(I_2(x)\) is the center pixel of the neighborhood area acquired in time \(T_2\). The similar situation will occur in \((1 - \partial_1) \times u_1^{\mu}\) while \(I_1(i) > I_2(i)\).

To overcome this issue, we consider the INR shown as Equation (16)

\[
\text{DINR}^{\mu}(x) = \frac{\min\{\partial_1 I_1(x), \partial_2 I_2(x)\} + u_1^{\mu}}{\max\{\partial_1 I_1(x), \partial_2 I_2(x)\} + u_2^{\mu}}
\]  

(16)

where \(u_1^{\mu} = \frac{1}{N' - 1} \sum_{i \notin \Omega_{i}, \Omega_{x}} \min\{(1 - \partial_1)I_1(i), (1 - \partial_2)I_2(i)\}\), \(u_2^{\mu} = \frac{1}{N' - 1} \sum_{i \notin \Omega_{i}, \Omega_{x}} \max\{(1 - \partial_1)I_1(i), (1 - \partial_2)I_2(i)\}\). This equation has solved the above problem. However, if \((1 - \partial_1)I_1(i) > (1 - \partial_2)I_2(i)\) and \(\partial_1 I_1(x) < \partial_2 I_2(x)\), \(I_1(x)\) and \(I_2(i)\) are used to calculate the numerator while the former comes from the image obtained in time \(T_1\) and the latter comes from the image obtained in time \(T_2\). Thus, numerator and denominator are both calculated by using the mixed pixels acquired in time \(T_1\) and \(T_2\), and they are unreasonably used in change detection.

To solve the above problem, we consider the INR shown as Equations (17) and (18):
\[
DINR^m(x) = \frac{\partial p \times I_p(x) + (1 - \partial p)/(N' - 1) \times \sum_{i \in \Omega^+ \setminus x} I_p(i)}{\partial q \times I_q(x) + (1 - \partial q)/(N' - 1) \times \sum_{i \in \Omega^- \setminus x} I_q(i)}
\]  

(17)

\[
p = \begin{cases} 
1, & I_1(x) < I_2(x) \\
2, & I_1(x) > I_2(x)
\end{cases}
\]

\[
q = \begin{cases} 
1, & I_1(x) > I_2(x) \\
2, & I_1(x) < I_2(x)
\end{cases}
\]

(18)

This method can solve the aforementioned two issues. However, experimental results show that \(DINR^m(x)\) may be larger than 1 which is inconsistent with our intention that using the form \(\min(\cdot)/\max(\cdot)\) to distinguish both increasing and decreasing radiometries with any single threshold algorithm. Then, we developed the Equation (9) to avoid the aforementioned issues. In order to make the dynamic range of heterogeneity weight to be \([0, 1]\), we use Equation (10) to normalize it and get the INR shown as Equation (11). To guarantee the numerical stability while the denominator is close to zero, we get the final form of INR, presented in Equation (12), by exploiting a constant \(C\).