Change detection using distance-based algorithms between synthetic aperture radar polarimetric decompositions

Amir Najafi, Mahdi Hasanlou & Vahid Akbari

To cite this article: Amir Najafi, Mahdi Hasanlou & Vahid Akbari (2019): Change detection using distance-based algorithms between synthetic aperture radar polarimetric decompositions, International Journal of Remote Sensing

To link to this article: https://doi.org/10.1080/01431161.2019.1587202

Published online: 07 Mar 2019.
Change detection using distance-based algorithms between synthetic aperture radar polarimetric decompositions

Amir Najafi 🅰, Mahdi Hasanlou 🅰 and Vahid Akbari 🅱

东盟 School of Surveying and Geospatial Engineering, College of Engineering, University of Tehran, Tehran, Iran; 🅱Department of Physics and Technology, UiT The Arctic University of Norway, Tromsø, Norway

ABSTRACT
The present study introduces distance based change detection (CD) algorithms in polarimetric synthetic aperture radar (PolSAR) data. PolSAR images, due to interactions between electromagnetic waves and target and because of the high spatial resolution, can be used to study changes in the Earth’s surface. The purpose of this paper is to use features extracted from the fully-polarimetry imaging radar that involved Yamaguchi four-component and H/A/α decomposition based on the distance between the vectors of features for CD. We first extract features from polarimetric decompositions of multi-looked covariance (or coherency) matrix data. We then use two well-known distance measures namely Canberra and Euclidean distances for measuring the similarity between the vectors of polarimetric decompositions at different times. Assessment of incorporated methods is performed using different criteria, such as overall accuracy, area under the receiver operating characteristic curve, and false alarms rate. The results of the experiments show that Canberra distance has better performance with high overall accuracy and low false alarm rate than Euclidean distance and other compared algorithms to detect changes.

ARTICLE HISTORY
Received 16 June 2018
Accepted 30 December 2018

1. Introduction
Change detection (CD) in remote sensing is processed to analyze and identify changes in the same geographic area at different times (Hasanlou and Seydi 2018a; Radke et al. 2005). Synthetic aperture radar (SAR) sensors, operating independently of weather conditions and daylight, are widely used for CD (Hu and Ban 2014; Akbari et al. 2016). In addition, these images include an inherent speckle noise that must be suppressed before any further processing (Gong et al. 2016). PolSAR data are one of the important generations of remotely sensed images that are used in various applications. These images have the combination of the backscattering linear receiver and transmit polarization in four channels that involved: HH (Horizontal transmit and Horizontal receive), HV (Horizontal transmit and Vertical receive), VH (Vertical transmit and Horizontal receive), and VV (Vertical transmit and Vertical receive), from which different scattering mechanisms (surface, double-bounce, and volume
scattering) can be extracted (Akbari et al. 2016). By investigating this characteristic, various information can be extracted from the physical nature of the land cover characteristics in different polarizations (Lee and Pottier 2009). In this regard, incorporating decomposition of PolSAR images may be beneficial and improve the results of the CD (Huang et al. 2017). CD in remote sensing is generally performed in three main steps: (1) preprocessing images including co-registration and speckle noise reduction; (2) computing a difference image (DI); and (3) making a decision based on analysis of the difference image computed in the step two and preparing change and no-change classes (Akbari 2013).

Many researches have demonstrated the potential of SAR images in CD. The purpose of this paper is to use the produced and extracted features from PolSAR and then to detect change areas by combing some distance metrics and producing some of the features. Hence, the literature on CD with PolSAR data is sparser. Baroni et al. used the Principal Component Analysis (PCA) on HH, VV and HV channels of multi-temporal PolSAR collected during the National Aeronautics and Space Administration (NASA) Multi-Sensor Aircraft Campaign (MAC). This algorithm takes a lot of time to implement (Baronti et al. 1994). Yakoub Bazi et al. presented a novel automatic CD approach that used the single-channel single-polarization SAR images. To this end, the authors used the Log-Ratio operator for comparison between multi-temporal images and made the change map based on the modified Kittler–Illingworth (K&I) (Kittler and Illingworth 1986) threshold and generalized Gaussian model for modeling the distributions of changed and no-changed classes (Bazi, Bruzzone, and Melgani 2005). Marino et al. developed a target detector based on Polarimetric Fork (PF) of the single targets (Huynen parameters or \( \alpha \) angle). The detector was implemented for multiple reflections (odd and even bounces) and oriented dipoles. The detector was also compared with a Polarimetric Whitening Filter (PWF). The presented algorithm developed suitable validation and performance for embedded targets (Marino, Cloude, and Woodhouse 2010). Tang et al. extracted the Yamaguchi four-component decomposition from quad polarimetric RADARSAT-2 images and generated the change map by the Log-Ratio of double bounce features from this dataset at different times. The K&I algorithm is finally used to separate change and no-change classes (Tang et al. 2012). Liu et al. incorporated segmentation of images with the K&I minimum-error thresholding algorithm and distance measurement for measuring the distance between texture features at different times and finally detected changes in PolSAR images (Liu et al. 2012). Marino et al. presented a new polarimetric change detector based on the partial targets in the first acquisition as a reference target and for detecting the second acquisition. Angle difference was defined as thresholding, which was achieved from the eigenvector model for the coherency matrix. This detector was implemented on a variety of datasets. This detector was compared the Maximum Likelihood (ML) ratio. The results of this detector are suitable because, in the presented detector, the overall amplitude of the back-scattering is neglected (Marino, Cloude, and Lopez-Sanchez 2013). Quan et al. incorporated the Freeman-Durden decomposition to extract the polarization scattering characteristics of different objects. Then, the refined Lee filter was applied to reduce the speckle noise. Finally, an improved distance measurement of CD was proposed for multi-temporal PolSAR data (Quan et al. 2015). Qi et al. used the three-component algorithms that include decomposition of PolSAR images in multi-temporal format and
hierarchically segmented these images to define land parcels. They finally applied change vector analysis on a coherency matrix to detect the changed pixels and used post classification procedures on these images to identify land cover types and change map (Qi et al. 2015). Ratha et al. produced change maps based on the measurement of the geodesic distance using the observed Kennaugh matrix of the span and intensity features from the decomposition of PolSAR images (Ratha et al. 2017). As shown in the literature, current algorithms for CD with PolSAR data take a lot of time to be implemented. Moreover, in the literature, the researchers used the single feature to CD but in this paper, we used the combination of features for CD (combination of Yamaguchi four-component decomposition and H/A/α decomposition as the cube form of features).

The main objective of this paper is to apply two well-known distance measures, namely Canberra distance (CAD) and Euclidean distance (ED), as metric test statistics to measure the distance between polarimetric target decompositions (PTDs). The distance measures are used to contrast two vectors of polarimetric decompositions at different times and produce a scalar value, to which a threshold can be applied. In fact, we use the different PTD methods (Yamaguchi four-component and H/A/α decompositions) as input for measuring the similarity using the CAD and ED methods. In other words, the significance of the proposed method related to this integration. We compare the CD results obtained from our proposed method with the Hotelling-Lawley Trace (HLT) proposed by Akbari et al. (2016). We test the performance of distance measures for CD based on polarimetric decompositions extracted from multi-looked airborne Uninhabited Aerial Vehicle Synthetic Aperture Radar (UAVSAR) images.

2. Theory

This section consists of three parts. The first part explains the structure of PolSAR data. The second part describes the theory of polarimetric target decomposition, and the third part is a review of the Otsu image segmentation algorithm.

2.1. Polarimetric SAR

A fully-polarimetric imaging radar measures the amplitude and phase of backscattered signals that consist of four linear receiver and transmit polarizations (HH, HV, VH, and VV). These signals are used to form a $2 \times 2$ complex scattering matrix at each resolution cell on the ground (Lee and Pottier 2009). The measured PolSAR data can be mathematically written as a scattering matrix Equation (1):

$$
S = \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix}
$$

where $S_{hv}$ is a complex-valued measurement. Based on two important basic sets, lexicographic and Pauli, the following scattering vectors, $k_l$ and $k_p$, in each case are obtained under the assumption of the reciprocity theorem, $S_{hv} = S_{vh}$ for a monostatic observation Equation (2):

$$
k_l = \begin{bmatrix} S_{hh} \\ \sqrt{2} S_{hv} \\ S_{vv} \end{bmatrix}, \quad k_p = \frac{1}{\sqrt{2}} \begin{bmatrix} S_{hh} + S_{vv} \\ S_{hh} - S_{vv} \\ 2 S_{vh} \end{bmatrix}
$$
$S_{hv}$ is a coherent average of the HV and VH channel measurements and $\sqrt{2}$ arises from the requirement to conserve the total scattered power, after coherent averaging of the cross polarization channels (Lee et al. 1998). The polarimetric covariance and coherency matrix can be formed by computing the spatial average of the outer-product of the lexicographic and Pauli scattering vectors, respectively, Equation (3):

$$C = \langle k_i k_i^H \rangle$$

$$T = \langle k_p k_p^H \rangle$$

Here, $\langle \cdot \rangle^H$ means the Hermitian transposition operator and $\langle \cdot \rangle$ denotes a spatial ensemble average. Coherency or covariance matrices are used as input to polarimetric target decompositions (Lee and Pottier 2009).

### 2.2. Polarimetric SAR decompositions

PTD is an advanced technique for extracting more detailed and quantitative physical information to characterize the scattering mechanism of different ground targets. Many PTD techniques (Cloude and Pottier 1997; Freeman and Durden 1998; Touzi 2007; Yamaguchi et al. 2005) have been proposed for the interpretation of target scattering mechanisms using the coherency and covariance matrices. In this study, the two most well-known polarimetric decompositions, namely Yamaguchi four-component and $H/A/\alpha$ decompositions, are used to investigate the effect of different decomposition features for the PolSAR CD.

Yamaguchi et al. proposed an extension of the four-component model that involves non-reflection symmetric cases (Yamaguchi et al. 2005). This approach consists of four components: helix, surface, double bounce, and volume scattering. The helix scattering includes terrain reflection asymmetry that can be introduced by man-made structures or urban feature orientation. The covariance matrix ($C_Y$) of Yamaguchi is expressed as the combination of these four components in Equation (5):

$$\langle C_Y \rangle = P_s C_s + P_d C_d + P_v C_v + P_h C_h$$

where $P_s$, $P_d$, $P_v$ and $P_h$ are the coefficients of single, double bounce, volume and helix scattering, respectively, and $C_s$, $C_d$, $C_v$ and $C_h$ represent the covariance matrices of these four scattering mechanisms.

The $H/A/\alpha$ decomposition is based on eigenvectors and eigenvalues of the coherency matrix decomposition (Cloude and Pottier 1997). Eigenvector analysis provides information about different types of scattering processes, while eigenvalue analysis provides information about their relative magnitudes. Entropy ($H$) determines the degree of randomness of the distribution and is defined in the range of [0,1], where $H = 0$ indicates a single scattering mechanism and $H = 1$ indicates the random target scattering process and represents the completely depolarizing system. Anisotropy ($A$) parameter is an entropy complement, and its value indicates the relative importance of the second and third values. It is a useful parameter to improve the ability to detect various types of dispersion process. The alpha angle ($\alpha$) is the main parameter for identifying the dominant scattering mechanism. The value can be easily associated with the physics behind the scattering process involved. The range of this parameter is between $[0°,90°]$; $\alpha = 0°$ denotes odd bounce scattering, the values of $45°$ refer to
dipole scattering, and the $\alpha = 90^\circ$ corresponds to double-bounce scattering (Lee and Pottier 2009).

Equation (4), based on the eigenvectors of the coherency matrix, is written as follows, Equation (6) where $\mathbf{U}$ is the matrix of eigenvectors (note that $\mathbf{U}^{-1} = \mathbf{U}^\dagger$ for Hermitian symmetric matrices) and $\mathbf{\Lambda}$ is a diagonal matrix of the corresponding eigenvalues. The eigenvectors $\mathbf{u}$ share the same polarimetric bases as the input Pauli feature vectors. The $H/A/\alpha$ decomposition computes the following quantities from the set of eigenvectors and eigenvalues (the eigenvalues are assumed to be in the order of $\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq 0$), Equations (6)–(10):

$$
\mathbf{T} = \mathbf{U} \mathbf{\Lambda} \mathbf{U}^{-1} = \sum_{i=1}^{3} \lambda_i \mathbf{u}_i \mathbf{u}_i^\dagger
$$

(6)

$$
P_i = \frac{\lambda_i}{\sum_{i=1}^{3} \lambda_i} \quad 0 \leq P_i \leq 1
$$

(7)

$$
H = - \sum_{i=1}^{3} P_i \log_3 P_i \quad 0 \leq H \leq 1
$$

(8)

$$
A = \frac{\lambda_2 - \lambda_3}{\lambda_2 + \lambda_3} \quad 0 \leq A \leq 1
$$

(9)

$$
\alpha = \sum_{i=1}^{3} P_i \cos^{-1}(\mathbf{u}_i(1)) \quad 0^\circ \leq \alpha \leq 90^\circ
$$

(10)

2.3. The otsu algorithm

The Otsu algorithm is a thresholding method for automatic image clustering. The idea behind this approach is that the threshold value determines the weight of the variance within the minimum class value. The variance within the class is the variance of the total weight of each defined cluster according to Equation (11), (Otsu 1979):

$$
\sigma^2_{\text{within}}(t) = q_1(t) \sigma^2_1(t) + q_2 \sigma^2_2(t)
$$

(11)

where $\sigma^2_1(t)$ is the variance and $q_1(t)$ is the weight of each cluster defined based on Equation (12):

$$
q_1(t) = \sum_{i=t+1}^{f} P(i)
$$

(12)

where $P(i)$ is the probability of belonging to the class and $\sigma^2_1(t)$ is defined as Equation (14):

$$
\sigma^2_1(t) = \sum_{i=1}^{t} [(i - \mu_1(t))]^2 \frac{P(i)}{q_1(t)}
$$

(13)
\[ \mu_1(t) = \sum_{i=t+1}^{i} \frac{iP(i)}{q_1(t)} \]  

(14)

Let the gray level of a given image be divided into \( I \) values and the average gray level is also divided into the same \( I \) values. Finally, the variance within the class is calculated as Equation (15):

\[ \sigma^2_{\text{within}} = \sigma^2 - \sigma^2_{\text{within}}(t) \]  

(15)

Generally, the Otsu algorithm uses the following steps to select the threshold: (1) calculating histograms and probabilities, (2) calculating the initial value of the average and weights, (3) moving the threshold value to all possible probabilities, (4) updating average and weight, (5) calculating the variance within the class, and (6) finding the threshold with the most possible variance. This algorithm is widely used because it is simple, effective and adaptive. The algorithm has less computational time and maintains reasonable thresholding results (Hasanlou and Seyed Teymoor 2018b; Vala, Hetal, and Baxi 2013).

3. Change detection based on distance measures between polarimetric decompositions

In order to apply CD to PolSAR data, we need to use appropriate distance measures. We intend to measure the pairwise distance between polarimetric decompositions of two datasets acquired at different times. Considering that the study is carried out on urban areas, therefore, Yamaguchi four-component and \( H/A/\alpha \) decompositions are used. The inputs are two 7 dimensional vectors containing the elements of PTD, i.e. Yamaguchi and \( H/A/\alpha \) decompositions, at two different times, as Equations (16)–(17):

\[ X = [P^Y_s, P^Y_d, P^Y_v, P^Y_h, H, A, \alpha] \]  

(16)

\[ Y = [P^Y_s, P^Y_d, P^Y_v, P^Y_h, H, A, \alpha] \]  

(17)

where \( X \) is the input features at the time \( t_a \) and \( Y \) is the input features at the time \( t_b \). Each element of the \( X \) and \( Y \) vectors extracts features from the two subsets of the study areas. The correlation coefficient of each element is calculated and many of these elements have the least dependency on each other. According to the correlation coefficient, the dependency between different elements is less than one and therefore there is no redundancy. Figure 1 shows the correlation between the input features. Based on this figure, the used features in the 7 dimensional vectors for CD have minimum correlation and non-redundancy.

It is desirable that all the conditions of a general metric apply, so that

1. the distance must be non-negative, i.e. the distance is in the range of \([0,1]\),
2. the distance between two vectors is symmetric so that the distance between \( X \) and \( Y \) is equal to the distance between \( Y \) and \( X \),
3. if \( X = Y \), thus, the distance is equal to zero.

Two distance measures that meet these requirements are CAD and ED (or \( L_2 \) metric). CAD uses a numerical measure of the distance between pairs of points in a vector space,
which was first introduced by Lance and Williams (1966). It is a weighted version of $L_1$ (Manhattan) distance (Agarwal, Burgess, and Crammer 2009). CAD between the vectors $X$ and $Y$ in an $n$-dimensional real vector space are given as Equation (18):

$$\text{CAD}(X, Y) = \sum_{i=1}^{n} \frac{|x_i - y_i|}{|x_i| + |y_i|}$$ (18)

where $X$ and $Y$ are the corresponding vectors $x_i$ and $y_i$ are the numerical values of the pixels, $|\cdot|$ is the symbol of the absolute value and $n$ is the number of input features.

Another choice of distance-based algorithms between two temporal vectors of polarimetric decompositions is ED which is defined as the square root of the sum of the squared differences between the corresponding vectors (Beldarrain 2006). It is defined as Equation (19):

$$\text{ED}(X, Y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}$$ (19)

The general block diagram of the proposed CD approach is shown in Figure 2, which is made up of four main steps. (1) pre-processing: the matrix data of PolSAR datasets are co-registered and speckle-filtered with the refined Lee filter. This filter uses an edge-aligned window and applies local statistics in order to better preserve edge and spatial resolution as well as detail features. This filter is adaptive and preserves the scattering mechanism of each pixel; it is also very fast and simple and has no blurry image (Lee and Pottier 2009); (2) feature extraction: PTD features are extracted from the matrix data and normalized between [0,1] for each data, and also the extracted features are formed in vector form Equations (16)–(17). We use the $C$ matrix

Figure 1. Correlation Coefficient (CC) between input features.
for Yamaguchi four-component decomposition and the \( T \) matrix for \( H/A/\alpha \) decomposition; (3) computing distance-based methods: the distance-based algorithms described above are applied to the vector of extracted features from bi-temporal data to create DI; (4) making a decision based on the analysis of the distance-based methods computed in step three to test the hypotheses of change versus no-change. Several algorithms have been proposed in the literature to determine the threshold in a completely unsupervised manner. In this paper, we choose to apply the Otsu algorithm (Otsu 1979) on DI.

4. The study area and datasets

The study area of this dataset is located in the San Francisco city. Two L-band (with a wavelength of 23.84 cm and a frequency of 1.26 GHz) fully-polarimetric images are acquired by the Jet Propulsion Laboratory/National Aeronautics and Space Administration UAVSAR on 18 September 2009, and 11 May 2015. This airborne polarimetric repeat-pass interferometric radar system has obtained the data with a spatial resolution of 1.66m in the range and 1.00m in the azimuth direction. Incidence angles range from 25° to 65°. In this paper, two pairs of subset images are selected as the areas of interest from the full scene for the performance evaluation of the proposed CD. Figure 3 (a)–(b) and (c)–(d) show the RGB (Red: \(|HH - VV|\); Green: \(2|HV|\); Blue: \(|HH + VV|\)) Pauli images of the two subsets of the PolSAR scene. The first and second subsets are \(200 \times 200\) and \(100 \times 100\), respectively. Figure 3(e,f) show the reference test maps associated with these subsets, made for the quantitative analysis of the CD results. The reference test maps of the two subsets are generated by Google earth images and false color of radar images (Pauli images) at a different time. In fact, the regions labeled as change
and no-change in the reference test maps are extracted manually using these images and the comparison method. These two data sets can be found online in http://rslab.ut.ac.ir.

5. Experiments results

To evaluate the capability of the proposed change detectors, two cases are investigated. The first case shortly named C1, utilizes the CD methods without speckle filtering. The second case shortly named C2, utilizes CD methods filtered with the refined Lee filter. These two cases are compared in terms of CD performance of the CAD, ED and HLT algorithms.
Figure 4 shows the CD results of the proposed algorithms for both subsets under two different cases including filtered with the refined Lee (C1) and without filtering (C2). The change maps of the two subsets in the two cases for the CAD algorithm are shown in Figure 4(a)–(b) and (g)–(h). The change map outputs of the CAD algorithm are similar to the reference change map of two subsets. Further, the change maps of the ED algorithm are shown in Figure 4(c)–(d) and (i)–(j) for the two subsets in the designed cases. Table 1 provides a quantitative evaluation of the distance-based algorithms which contain the overall accuracy (OA), false alarm rate (FAR), and area under the curve (AUC) of the ROC (Metz 1978). Table 1 reports the values for both subsets under the two cases mentioned above. By comparing the quantitative results in Table 1, we can conclude that both the CAD and ED methods work slightly better when data are filtered with the refined Lee
filter. Moreover, both methods are better than the HLT method. It means that higher OA, lower FAR, and larger AUC is achieved for the filtered matrix data. By comparing the two distances, the CAD algorithm obtains higher detection rates, lower FARs, and larger AUCs. To further evaluate the performance of the change detectors, the ROC curves of the two tests are presented in Figure 5 which presents the hit (detection) rate as a function of FAR. The ROC plots of the CAD detector (red line) is above that of the ED detector (blue line) and HLT detector (green line), indicating better detection performance obtained from ED for both subsets. Figure 5(b,d) show again how the ROC curves are improved when filtering the matrix data. For comparing the proposed

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Scenario</th>
<th>OA (%)</th>
<th>FAR (%)</th>
<th>AUC</th>
<th>OA (%)</th>
<th>FAR (%)</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAD</td>
<td>C1</td>
<td>95.81</td>
<td>4.03</td>
<td>0.95</td>
<td>95.63</td>
<td>5.71</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td>C2</td>
<td>96.37</td>
<td>3.19</td>
<td>0.97</td>
<td>97.52</td>
<td>2.62</td>
<td>0.97</td>
</tr>
<tr>
<td>ED</td>
<td>C1</td>
<td>94.90</td>
<td>5.85</td>
<td>0.90</td>
<td>93.24</td>
<td>6.33</td>
<td>0.92</td>
</tr>
<tr>
<td></td>
<td>C2</td>
<td>96.05</td>
<td>4.95</td>
<td>0.93</td>
<td>95.19</td>
<td>5.54</td>
<td>0.95</td>
</tr>
<tr>
<td>HLT</td>
<td>C1</td>
<td>92.56</td>
<td>7.34</td>
<td>0.86</td>
<td>92.69</td>
<td>7.26</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td>C2</td>
<td>93.65</td>
<td>6.12</td>
<td>0.90</td>
<td>93.55</td>
<td>5.98</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Figure 5. ROC curve of both subsets under two different cases. (a) Subset 1 for C1. (b) Subset 1 for C2. (c) Subset 2 for C1. (d) Subset 2 for C2.
algorithm with the HLT method based on Table 1, the numerical results of this algorithm are lower than of the proposed distance algorithms. This algorithm has higher FAR but lowers OA and AUC than the proposed algorithms. Moreover, we compare the change maps of this algorithm in Figure 4(e)–(f) and (k)–(l) with the proposed distance algorithms. This algorithm does not show change and no-change regions the same as the proposed algorithms. The ROC curve of this algorithm (green line) is plotted in Figure 5. Comparing the ROC curves of this algorithm and the proposed distance algorithm shows that the HLT algorithms have high FAR but low AUC.

6. Conclusion

This paper implements and evaluates distance-based methods between polarimetric decompositions using bi-temporal polarimetric UAVSAR images. In this paper, the two most popular PTD features are first extracted for each speckle-filtered polarimetric matrix data. These features include Yamaguchi four-component and $H/A/\alpha$ decompositions extracted from covariance and coherency matrix data, respectively, and normalized between $[0,1]$ for each data. The extracted features are formed in vector mode based Equations (16)–(17). Then, two well-known distance-based algorithms, CAD and ED, are used to measure the similarity between two vectors of polarimetric decompositions at different times. CAD uses a numerical measure of the distance between pairs of points in a vector space. It is a weighted version of L1 (Manhattan) distance. ED (or L2 metric) is defined as the square root of the sum of the squared differences between the corresponding vectors. Moreover, as a part of this study, we compare the results of the proposed distance algorithms with the recently published HLT PolSAR change detector. According to numerical and visual results of the distance based algorithms, the proposed algorithms have better performances for CD. The CAD algorithm produces slightly higher OA, lower FAR, and larger AUC than the other algorithms. These algorithms are more suitable for CD than the HLT algorithm because of high FAR and low AUC. The proposed algorithms are very fast and simple for SAR CD applications.

Disclosure statement

No potential conflict of interest was reported by the authors.

ORCID

Amir Najafi http://orcid.org/0000-0003-1609-1835
Mahdi Hasanlou http://orcid.org/0000-0002-7254-4475
Vahid Akbari http://orcid.org/0000-0002-9621-8180

References


