A novel super-resolution method of PolSAR images based on target decomposition and polarimetric spatial correlation

Lamei Zhang\textsuperscript{a}, Bin Zou\textsuperscript{a}, Huijun Hao\textsuperscript{b} & Ye Zhang\textsuperscript{a}
\textsuperscript{a} Department of Information Engineering, Harbin Institute of Technology, Harbin, 150001, China
\textsuperscript{b} East China Research Institute of Electronic and Engineering, Hefei, 230031, China

Available online: 07 Jul 2011


To link to this article: http://dx.doi.org/10.1080/01431161.2010.492251

PLEASE SCROLL DOWN FOR ARTICLE

Full terms and conditions of use: http://www.tandfonline.com/page/terms-and-conditions

This article may be used for research, teaching, and private study purposes. Any substantial or systematic reproduction, redistribution, reselling, loan, sub-licensing, systematic supply, or distribution in any form to anyone is expressly forbidden.

The publisher does not give any warranty express or implied or make any representation that the contents will be complete or accurate or up to date. The accuracy of any instructions, formulae, and drug doses should be independently verified with primary sources. The publisher shall not be liable for any loss, actions, claims, proceedings, demand, or costs or damages whatsoever or howsoever caused arising directly or indirectly in connection with or arising out of the use of this material.
A novel super-resolution method of PolSAR images based on target decomposition and polarimetric spatial correlation

LAMEI ZHANG*,†, BIN ZOU†, HUIJUN HAO‡ and YE ZHANG†
†Department of Information Engineering, Harbin Institute of Technology, Harbin 150001, China
‡East China Research Institute of Electronic and Engineering, Hefei, 230031, China

(Received 06 April 2009; in final form 25 March 2010)

The polarimetric synthetic aperture radar (PolSAR) is becoming more and more popular in remote-sensing research areas. However, due to system limitations, such as bandwidth of the signal and the physical dimension of antennas, the resolution of PolSAR images cannot be compared with those of optical remote-sensing images. Super-resolution processing of PolSAR images is usually desired for PolSAR image applications, such as image interpretation and target detection. Usually, in a PolSAR image, each resolution contains several different scattering mechanisms. If these mechanisms can be allocated to different parts within one resolution cell, details of the images can be enhanced, which that means the resolution of the images is improved. In this article, a novel super-resolution algorithm for PolSAR images is proposed, in which polarimetric target decomposition and polarimetric spatial correlation are both taken into consideration. The super-resolution method, based on polarimetric spatial correlation (SRPSC), can make full use of the polarimetric spatial correlation to allocate different scattering mechanisms of PolSAR images. The advantage of SRPSC is that the phase information can be preserved in the processed PolSAR images. The proposed methods are demonstrated with the German Aerospace Center (DLR) Experimental SAR (E-SAR) L-band full polarized images of the Oberpfaffenhofen Test Site Area in Germany, obtained on 30 September 2000. The experimental results of the SRPSC confirms the effectiveness of the proposed methods. 1

1. Introduction

The polarimetric synthetic aperture radar (PolSAR), which can provide polarimetric characteristics of the scene using four channels, hh, hv, vh and vv, is becoming more and more popular in remote-sensing research areas. However, due to system limitations, such as bandwidth of signal and physical dimensions of antennas, the resolution of PolSAR images cannot be compared with those of optical remote-sensing images. Therefore, super-resolution processing of PolSAR images is usually desired for PolSAR image applications such as image interpretation and target detection.

*Corresponding author. Email: zzbei@hit.edu.cn
Now at: Post-doctoral Research Center in Instrument Science and Technology, Harbin Institute of Technology, Harbin 150001, China.
Backscattering from certain objects is strongly dependent on polarization, so some important joint scattering might be missed using only one single channel. Therefore, appropriate joint processing of polarimetric channels might provide a high signal to noise ratio (SNR) to achieve high super-resolution images. As a consequence, the joint application of polarimetric information and super-resolution techniques could reduce some undesirable properties of super-resolution techniques alone. Generally, in a PolSAR image, each resolution cell contains several different scattering mechanisms. Since each scattering mechanism may be derived from multiple scatterers, if these mechanisms can be allocated to different parts within one resolution cell, the details of the images can be enhanced, which means that the resolution of the images has been improved.

The resolution of SAR images, in range and azimuth, is limited by the transmitted signal bandwidth and the synthetic aperture length, respectively. To overcome this limitation, several algorithms have been conceived to obtain super-resolved radar images. The conventional fast Fourier transform (FFT) method is a nonparametric spectral-estimation approach and is efficient to reconstruct SAR images. However, the FFT method generates SAR images with high side lobes and poor resolutions due to the limited phase-history data collected from a finite-length synthetic aperture with finite bandwidth radar (Nuthalapati 1992, Gabriel 1993, Bi et al. 1999). By means of the spectral analysis (SPECAN) technique, raw radar data are transformed in a linear combination of two-dimensional sinusoids embedded in noise (Pastina et al. 1998, Bi et al. 1999). The nonparametric methods have been used for image formation and construction. The matched-filter-bank-based complex spectral-estimation methods including the Capon (Capon 1969, Benitz 1997) and amplitude and phase estimation (APES) (Li and Stoica 1996) methods. Yet, the resolution of these nonparametric methods is not significantly better than that of the FFT-based methods, due to their nonparametric nature. Parametric spectral-estimation algorithms have been used extensively for SAR construction due to the attractive alternative to nonparametric methods. Modern spectral analysis methods based on the auto-regressive (AR) models (Farina et al. 1994) are more effective than the FFT methods in estimating the amplitude and frequency values of the two-dimensional (2D) sinusoids. The multiple signal classification (MUSIC) (Odendaal et al. 1994), the matrix pencil (Hua 1994), the estimation of signal parameters via rotation invariant techniques (ESPRIT) (Barbarossa et al. 1996) and relaxation (RELAX) methods (Liu and Li 1998, Zhou et al. 2008) could be applied to the SAR images. These parametric methods are robust and offer the promise of significantly improving the resolution of SAR image.

The application of super-resolution technique using polarimetric SAR imaging was firstly introduced by Pastina et al. (2001, 2003). They used the super-resolution techniques for ship detection in polarimetric SAR images by introducing parametric spectral estimators. However, as a spectral-domain method, the characteristics of polarimetric SAR images are not fully extracted. Then, Chen and Yang (2007) constructed convex sets in the projection onto convex sets (POCS) method, by utilizing the multiplicative characteristics of noise, and detailed the proposed algorithm for ship targets in polarimetric SAR images. Both of these two classes of super-resolution processing of PolSAR images may provide higher resolution. However, the polarimetric information in the original images, which is very important for classification and recognition, is discarded. Suwa and Iwamoto (2003) have extended the concept of bandwidth extrapolation (BWE) to a polarimetric radar case and proposed an algorithm called polarimetric BWE (PBWE). Utilization of fully polarimetric information allows PBWE to improve the resolution beyond the conventional
BWE method. In addition, PBWE shows improved capability for maintaining the full polarization properties of the scatters. Then, Suwa and Iwamoto (2007) proposed a two-dimensional polarimetric bandwidth extrapolation (2D-PBWE), which uses a 2D polarimetric linear-prediction model and expands the spatial frequency bandwidth in range and azimuth directions simultaneously.

For polarimetric information extraction, the polarimetric target decomposition (PTD) theorem is a representative method. The PTD theorem expresses the average mechanism as the sum of independent elements in order to associate a physical mechanism with each resolution cell, which allows the identification and separation of scattering mechanisms in polarization signatures for the purposes of classification and parameter estimation. At present, two main classes of PTD can be identified. One is called coherent target decomposition (CTD), which is used to deal with decomposition of the scattering matrix. The other is called incoherent target decomposition (ICTD), which deals with coherency of covariance matrices. Detailed descriptions and comparisons of these theorems have been provided by Zhang et al. (2008a,b). Typical coherent decomposition theorems commonly refer to Pauli decomposition and sphere, diplane and helix (SDH) decomposition (Krogager et al. 1995, 1997). The scattering matrix can characterize the scattering process produced by a given target and therefore the target itself. This is possible only in those cases in which both the incident and the scattered waves are completely polarized waves. Consequently, CTD can be only employed to study the so-called coherent targets. In a real situation, the measured scattering matrix by the radar corresponds to a complex coherent target and, only on a few occasions, will the matrix correspond to a simpler or canonical object (e.g. the trihedral employed to calibrate SAR imagery). Nevertheless, in a general situation, a direct analysis of the scattering matrix, with the objective of inferring physical properties of the scatter under study, is known to be very difficult. Generally, conventional averaging and statistical method are applied to PolSAR images; therefore, incoherent approaches are frequently chosen for post-processing. Several decomposed methods have been proposed to identify the scattering characteristics based on polarimetric statistical characteristics (Cloude and Pottier 1996). For natural terrain, Freeman and Durden (1998) proposed a three-component scattering model (generally called Freeman decomposition), which decomposed the measured covariance matrix into single-bounce, double-bounce and volume-scattering contributions based on a physical scattering model. Then, Moriyama et al. (2005) presented an odd-bounce, even-bounce and cross (OEC) scattering model to represent the polarimetric radar signal from urban areas. Yamaguchi and Moriyama (2005) and Yamaguchi et al. (2006) extended Freeman decomposition to a four-component scattering model, in which they added helix scattering as the fourth component to Freeman decomposition to analyse urban areas. Accordingly, Zhang et al. (2008a,b, 2009) proposed a general multiple-component scattering model (MCSM) to analyse PolSAR images, which was suitable for both natural terrain and human-made areas.

In this article, novel super-resolution algorithms for PolSAR image processing are proposed, in which PTD and polarimetric spatial correlation are both taken into consideration and polarimetric information can still be preserved during processing. The processing mainly consists of three steps. In the first step, different scattering components are obtained by PTD. In this article, we concentrate our discussion on Pauli decomposition. The result of SDH decomposition, Freeman decomposition and OEC decomposition are also given. The next step is to find out the distribution of different scattering components within each resolution cell based on polarimetric spatial correlation. Then, the super-resolution image of each component is obtained according
to the spatial distribution in the adjacent area. Subsequently, the super-resolution PolSAR image is obtained based on CTD and polarimetric spatial correlation.

2. Polarimetric target decomposition

In this section, we just describe some classical decomposition methods, which will be used in the proposed super-resolution approach. Pauli decomposition and SDH decomposition of CTD, as well as Freeman decomposition and OEC decomposition of ICTD, are summarized below.

2.1 Coherent target decomposition

Full polarimetric SAR systems measure a $2 \times 2$ complex scattering matrix $S$ associated with each resolution cell in the image. In the form of scattering matrices, a single-look SAR image can be expressed as follows:

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

where $S_{ij}$ ($i,j = h,v$) are the scattering coefficients when transmitting in $j$ polarization and scattering in $i$ polarization, and $h$ and $v$ stand for horizontal and vertical polarization, respectively. The scattering coefficients are defined as the ratio of the transmitted electric-field vector (complex amplitude) and the scattered electric-field vector.

The objective of the coherent decompositions is to express the measured scattering matrix $S$ by the radar as the combination of the scattering responses of simpler objects, each of which corresponds to a certain scattering mechanism:

$$ S = \sum_{i=1}^{m} c^i S^i = c^1 S^1 + \cdots + c^i S^i + \cdots + c^m S^m, $$

where $S^i$ stands for the response of some simple objects, also known as canonical objects, whereas $c^i$ denotes the corresponding weight of different scattering mechanisms in the combination. As observed in equation (2), the term combination refers to the weighted addition of the $m$ scattering matrices. In order to simplify the understanding of equation (2), it is desirable that the matrices $S^i$ have the property of independence among them to avoid a particular scattering behaviour being present in more than one matrix.

2.1.1 Pauli decomposition. The most commonly known and applied coherent decomposition is Pauli decomposition. Pauli decomposition expresses the measured scattering matrix $S$ in so-called Pauli bases. If we consider the conventional orthogonal linear ($h,v$)basis, in a general case, the Pauli bases $\{S_a, S_b, S_c, S_d\}$ are given by the following four $2 \times 2$ matrices:

$$ S_a = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad S_b = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}, \quad S_c = \frac{1}{\sqrt{2}} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \quad \text{and} \quad S_d = \frac{1}{\sqrt{2}} \begin{bmatrix} 0 & -j \\ j & 0 \end{bmatrix}, $$

where $j$ is the imaginary unit, which equals to the square root of $-1$.

In the case of backscattering in a reciprocal medium, according to the reciprocity theorem, i.e. $S_{hv} = S_{vh}$, the Pauli bases $\{S_a, S_b, S_c, S_d\}$ can be reduced to $\{S_a, S_b, S_c\}$. 
Consequently, Pauli decomposition is given by the following expression, in which the scattering matrix $S$ can be expressed as:

$$\mathbf{S} = \alpha \mathbf{S}_a + \beta \mathbf{S}_b + \gamma \mathbf{S}_c \Leftrightarrow \begin{bmatrix} S_{hh} & S_{hv} \\ S_{vh} & S_{vv} \end{bmatrix} = \alpha \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \beta \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} + \gamma \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}.$$  \tag{4}

where $\alpha = (S_{hh} + S_{vv}) / \sqrt{2}$, $\beta = (S_{hh} - S_{vv}) / \sqrt{2}$ and $\gamma = \sqrt{2}S_{hv}$.

The matrix $\mathbf{S}_a$ corresponds to the scattering matrix of a sphere, a plate or a trihedral. In general, $\mathbf{S}_a$ is referred to as single- or odd-bounce scattering. Thus, the complex coefficient $\alpha$ represents the contribution of $\mathbf{S}_a$ to the final measured scattering matrix $\mathbf{S}$. The intensity of this coefficient $|\alpha|^2$ determines the power scattered by targets characterized by single or odd bounces. The second matrix $\mathbf{S}_b$ represents the scattering mechanism of a dihedral oriented at $0^\circ$. In general, this component indicates a scattering mechanism characterized by double or even bounce, since the polarization of the returned wave is mirrored with respect to that of the incident wave. Consequently, $\beta$ stands for the complex coefficient of this scattering mechanism and $|\beta|^2$ represents the scattering power by this type of target. The third matrix $\mathbf{S}_c$ corresponds to the scattering mechanism of a diplane oriented at $45^\circ$. From a qualitative point of view, the scattering mechanism represented by $\mathbf{S}_c$ is referred to as those scatterers that are able to return the orthogonal polarization. The coefficient $\gamma$ represents the contribution of $\mathbf{S}_c$ to $\mathbf{S}$, whereas $|\gamma|^2$ stands for the scattered power by this type of scatterers.

### 2.1.2 Sphere, diplane and helix decomposition.

According to Krogager et al., the complex symmetric scattering matrix can be decomposed into three components on the circular basis $(r,l)$, corresponding to a sphere, a diplane and a right-wound or left-wound helix, respectively (Krogager and Czyz 1995, Krogager et al. 1997):

$$\begin{bmatrix} S_{rr} & S_{rl} \\ S_{lr} & S_{ll} \end{bmatrix} = \begin{bmatrix} |S_{rr}| \exp^{i\varphi} \exp^{i\psi} & |S_{rl}| \exp^{i\psi} \\ |S_{lr}| \exp^{i\psi} & |S_{ll}| \exp^{i(\psi + \pi)} \end{bmatrix} = \begin{bmatrix} \exp^{i\varphi \psi} & 0 \\ 0 & 1 \end{bmatrix} + k_d \begin{bmatrix} \exp^{i2\theta} & 0 \\ 0 & \exp^{-i2\theta} \end{bmatrix} + k_h^+ \begin{bmatrix} \exp^{i2\phi} & 0 \\ 0 & 0 \end{bmatrix} \text{ (right-wound)},$$

$$= \begin{bmatrix} \exp^{i\varphi \psi} & 0 \\ 0 & 1 \end{bmatrix} + k_d \begin{bmatrix} \exp^{i2\theta} & 0 \\ 0 & \exp^{-i2\theta} \end{bmatrix} + k_h^- \begin{bmatrix} 0 & 0 \\ 0 & \exp^{-i2\phi} \end{bmatrix} \text{ (left-wound)}.$$  \tag{5}

where $r$ and $l$ mean right and left circular, respectively, and $j$ is the imaginary unit, which is equal to the square root of $-1$. The SDH decomposition presents six independent parameters, i.e. the three angles $\varphi, \varphi_s$ and $\theta$ and the three real coefficients $k_s, k_d$ and $k_h$. The phase $\varphi$ is referred as the absolute phase, whose value depends on the distance between the radar and the target under study. The parameters $\varphi_s$ and $k_s$ characterize the sphere component of the SDH decomposition. The phase $\varphi_s$ represents a displacement of the sphere with respect to the diplane and the helix components, and the real parameter $k_s$ represents the contribution of the sphere components to the final scattering matrix $\mathbf{S}$. Consequently, $|k_s|^2$ is interpreted as the power scattered by the sphere-like component of the matrix $\mathbf{S}$. The phase parameter $\theta$ stands for the orientation angle of the diplane and the helix components of the SDH decomposition. The coefficients $k_d$ and $k_h$ correspond to the weights of the diplane and the helix components. Thus, $|k_d|^2$ and $|k_h|^2$ are interpreted as the power scattered by the diplane- and helix-like components of the SDH decomposition. Due to the arbitrary value that
this phase can present, it is often considered that the SDH decomposition presents five independent parameters given by \( \{ \phi_s, \theta, k_s, k_d, k_h \} \) plus the absolute phase given by \( \varphi \).

The coefficients are easily obtained from the elements in the circular basis:

\[
\begin{align*}
    k_s &= |S_{rl}| \\
    k_d^+ &= |S_{ll}| \\
    k_h^- &= |S_{rr}|-|S_{rl}|
\end{align*}
\]

(left-wound) or

\[
\begin{align*}
    k_s &= |S_{rl}| \\
    k_d^- &= |S_{rr}| \\
    k_h^+ &= |S_{ll}|-|S_{rr}|
\end{align*}
\]

(right-wound) . \hspace{1cm} (6)

The phase components are:

\[
\begin{align*}
    \varphi &= \frac{1}{2} (\phi_{rr} + \phi_{ll} - \pi) , \\
    \theta &= \frac{1}{4} (\phi_{rr} - \phi_{ll} + \pi) , \\
    \phi_s &= \phi_{rl} - \frac{1}{2} (\phi_{rr} + \phi_{ll}) . \hspace{1cm} (7)
\end{align*}
\]

Because helix scattering is a general scattering mechanism, which appears in urban area and disappears for almost all natural distributed areas, SDH decomposition can distinguish man-made targets from natural targets (Zhang et al. 2008a,b).

2.2 Incoherent target decomposition

As explained previously, the scattering matrix is only able to characterize the so-called coherent or pure scatterers. On the other hand, this matrix cannot be employed to characterize the so-called distributed scatterers. This type of scatterers can only be characterized statistically due to the presence of speckle noise. Second-order polarimetric representations can be employed to analyse distributed scatterers. These second-order descriptors are the Hermitian average covariance matrix \( \langle C \rangle \) and the coherency matrix \( \langle T \rangle \). These two representations of the polarimetric information are equivalent. In this article, we focus on the decomposition theorems using the covariance matrix.

The scattering matrix could be expressed as an equivalent scattering vector. In the case of backscattering in a reciprocal medium, according to the reciprocity theorem, the three-dimensional lexicographic scattering vector \( k_L \) is obtained as:

\[
k_L = \left[ S_{hh}, \sqrt{2} S_{hv}, S_{vv} \right]^T , \hspace{1cm} (8)
\]

where superscript T denotes the transposition operation.

To derive the polarimetric scattering characteristics contained in the PolSAR image, it is necessary to evaluate the second-order statistics of its scattering matrices. Using the outer product of the scattering vector \( k_L \), we can define the covariance matrix \( \langle \cdot \rangle \) as:

\[
\langle C \rangle = \langle k_L k_L^T \rangle = \begin{bmatrix}
    \left\langle S_{hh} S_{hh}^* \right\rangle & \sqrt{2} \left\langle S_{hh} S_{hv}^* \right\rangle & \left\langle S_{hh} S_{vv}^* \right\rangle \\
    \sqrt{2} \left\langle S_{hv} S_{hh}^* \right\rangle & 2 \left\langle S_{hv} S_{hv}^* \right\rangle & \sqrt{2} \left\langle S_{hv} S_{vv}^* \right\rangle \\
    \left\langle S_{vv} S_{hh}^* \right\rangle & \sqrt{2} \left\langle S_{vv} S_{hv}^* \right\rangle & \left\langle S_{vv} S_{vv}^* \right\rangle
\end{bmatrix} , \hspace{1cm} (9)
\]

where \( \langle \cdot \rangle \) denotes the ensemble average in the data processing and the superscript * denotes complex conjugation. The covariance matrix is directly related to measurable radar parameters and is more straightforward to understand physically.
The complexity of the scattering process makes the physical study of a given scatterer extremely difficult through the direct analysis of $\langle C \rangle$. Hence, the objective of the incoherent decompositions is to separate the $\langle C \rangle$ matrices as the combination of second-order descriptors corresponding to simpler or canonical objects, presenting an easier physical interpretation. These decomposition theorems can be expressed as:

$$\langle C \rangle = \sum_{i=1}^{m} c^i C^i = c^1 C^1 + \cdots + c^i C^i + \cdots + c^m C^m,$$

where the canonical responses are represented by $C^i$, and $c^i$ denotes the coefficients of these components in $\langle C \rangle$.

As in the case of the coherent decomposition, it is desirable that these components present some properties. First of all, it is desirable that the components $C^i$ correspond to pure targets in order to simplify the physical study. Nevertheless, this is not absolutely necessary. The bases in which $\langle C \rangle$ is decomposed, i.e. $\{ C^i, i = 1, \ldots, m \}$ is not unique. Consequently, different decompositions can be represented.

Several incoherent decomposition methods have been proposed to identify the scattering characteristics based on polarimetric statistical characteristics (Cloude and Pottier 1996). In this category, we discuss two typical incoherent decomposition theorems: Freeman decomposition (Freeman and Durden 1998) and OEC decomposition (Moriyama et al. 2005).

### 2.2.1 Freeman decomposition

Freeman and Durden (1998) proposed a three-component scattering model in which the covariance matrix $\langle C \rangle$ of polarimetric SAR data is decomposed for information extraction. Freeman decomposition describes scattering mechanisms as three physical mechanisms, namely, surface scattering, double-bounce scattering and volume scattering:

$$\langle C \rangle = f_{\text{surface}} C_{\text{surface}} + f_{\text{double}} C_{\text{double}} + f_{\text{volume}} C_{\text{volume}},$$

where $\beta$ is a ratio of hh backscattering to vv backscattering of single-bounce scattering, $\alpha$ is a similar coefficient to $\beta$ (Freeman and Durden 1998). $f_{\text{surface}}$, $f_{\text{double}}$ and $f_{\text{volume}}$ are the coefficients of single-bounce, double-bounce and volume-scattering components, respectively, and $C_{\text{surface}}$, $C_{\text{double}}$ and $C_{\text{volume}}$ represent the corresponding covariance bases. According to this model, the measured power may be decomposed into three quantities:

$$P_{\text{surface}} = f_{\text{surface}} \left(1 + |\beta|^2\right),$$

$$P_{\text{double}} = f_{\text{double}} \left(1 + |\alpha|^2\right),$$

$$P_{\text{volume}} = \frac{8}{3} f_{\text{volume}},$$

$$P = P_{\text{surface}} + P_{\text{double}} + P_{\text{volume}}.$$
This method is based on simple physical scattering mechanisms (surface scattering, double-bounce scattering and volume scattering). The contributions of each of the three scattering mechanisms to the total power for each pixel, with surface scattering coloured blue, volume scattering coloured green and double-bounce scattering coloured red, are shown in figure 5 in a later section.

\[ \langle S_{\text{hh}}S^*_{\text{hv}} \rangle \approx \langle S_{\text{vv}}S^*_{\text{hv}} \rangle \approx 0. \]

2.2.2 Odd-bounce, even-bounce and cross decomposition. For urban areas, the reflection symmetry condition does not hold, and it is necessary to take the effect of \( \langle S_{\text{hh}}S^*_{\text{hv}} \rangle \neq 0 \) and \( \langle S_{\text{vv}}S^*_{\text{hv}} \rangle \neq 0 \) into account. Moriyama et al. (2005) proposed a model for urban-area information extraction. The model decomposes the covariance matrix into three kinds of scattering mechanisms, namely odd-bounce scattering, even-bounce scattering and cross scattering:

\[
\langle C \rangle = f_{\text{odd}} C_{\text{odd}} + f_{\text{even}} C_{\text{even}} + f_{\text{cross}} C_{\text{cross}} = f_{\text{odd}} \begin{bmatrix} |\beta|^2 & 0 & \beta \\ 0 & 0 & 0 \\ \beta^* & 0 & 1 \end{bmatrix} + f_{\text{even}} \begin{bmatrix} |\alpha|^2 & 0 & \alpha \\ 0 & 0 & 0 \\ \alpha^* & 0 & 1 \end{bmatrix} + f_{\text{cross}} \begin{bmatrix} |\gamma|^2 & \sqrt{2} \gamma \rho^* & \gamma \\ \sqrt{2} \gamma^* \rho & 2 |\rho|^2 & \sqrt{2} \rho \\ \gamma^* & \sqrt{2} \rho^* & 1 \end{bmatrix},
\]

where \( \gamma \) and \( \rho \) are the ratio of hh and hv backscattering to vv backscattering, \( f_{\text{odd}}, f_{\text{even}} \) and \( f_{\text{cross}} \) represent the weight of odd-bounce scattering, even-bounce scattering and cross scattering, respectively, and \( C_{\text{odd}}, C_{\text{even}} \) and \( C_{\text{cross}} \) represent the corresponding covariance bases. Then, the power of each term \( P_{\text{odd}}, P_{\text{even}} \) and \( P_{\text{cross}} \) can be calculated. \( P \) is the total power:

\[
P_{\text{odd}} = f_{\text{odd}} \left( 1 + |\beta|^2 \right), \\
P_{\text{even}} = f_{\text{even}} \left( 1 + |\alpha|^2 \right), \\
P_{\text{cross}} = f_{\text{cross}} \left( 1 + |\gamma|^2 + 2 |\rho|^2 \right), \\
P = P_{\text{odd}} + P_{\text{even}} + P_{\text{cross}}. \]

In urban areas, buildings have strong even-bounce scattering characteristics, and their information can be easily extracted from the even-bounce scattering component.

3. A super-resolution algorithm based on polarimetric spatial correlation

Generally, in remote-sensing images, the adjacent pixels are more likely to come from the same scattering mechanism, and the most common relationships of adjacent pixels in remote-sensing images are quadrant pixels. Zou et al. (2008) proposed a super-resolution method based on target decomposition and quadrant pixel (SRQP). In section 3.1, a brief description of the SRQP is summarized. Actually, neighbouring pixels in PolSAR images have higher spatial correlation (Mertens et al. 2004). According to polarimetric spatial correlation, a novel super-resolution based on polarimetric spatial correlation (SRPSC) is proposed in section 3.2, a detailed solution procedure of the SRPSC is described in section 3.3 and an evaluation criterion of super-resolution method is discussed in section 3.4. In the following paragraphs, we use the CTD as an example to describe the detailed expression of these super-resolution methods.
3.1 Brief description of the super-resolution method based on target decomposition and quadrant pixel

Figure 1 is a sketch map of the SRQP. $A_5$ (shaded) is supposed to be the pixel to be processed with super-resolution, and which is divided into four sub-pixels $A_{5k}$ ($k = 1, 2, 3, 4$). We use a $3 \times 3$ window to describe the SRQP. In the $3 \times 3$ processing window, the coefficients in each pixel are $c_j^i$ ($j = 1, 2, \ldots, 9$), where $i$ is the number of the scattering mechanism in PTD and $j$ is the sequence number of the pixel in the processing window. The power of each scattering mechanism in the window $P_j^i$ ($j = 1, 2, \ldots, 9$) is defined as $P_j^i = |c_j^i|^2$ ($j = 1, 2, \ldots, 9$). Obviously, the neighbouring pixels in the same quadrant have a stronger influence on the sub-pixels. Then, according to the influence of neighbouring pixels, the coefficients, $c_{51}^i$, $c_{52}^i$, $c_{53}^i$ and $c_{54}^i$, of the sub-pixel can be determined, respectively, by:

\[
\begin{align*}
    c_{51}^i &= \frac{P_1^i + P_2^i + P_4^i}{P_t} c_5^i, \\
    c_{52}^i &= \frac{P_2^i + P_3^i + P_6^i}{P_t} c_5^i, \\
    c_{53}^i &= \frac{P_4^i + P_5^i + P_8^i}{P_t} c_5^i, \\
    c_{54}^i &= \frac{P_6^i + P_8^i + P_9^i}{P_t} c_5^i,
\end{align*}
\]

(15)

where $P_t^i$ is the weighted total power of all pixels in the window.

The four sub-pixels $A_{5k}$ ($k = 1, 2, 3, 4$) are derived from the low-resolution pixel $A_5$, so they must satisfy $c_{51}^i + c_{52}^i + c_{53}^i + c_{54}^i = c_5^i$. Then, the weighted total power of all pixels in the window $P_t^i$ in equation (15) can be described as:

\[
P_t^i = P_1^i + P_3^i + P_7^i + P_9^i + 2 \left( P_2^i + P_4^i + P_6^i + P_8^i \right).
\]

(16)

Therefore, the super-resolution processing of the $i$th scattering mechanism of $A_5$ is completed. We can get the super-resolved sub-pixels in the same way for other pixels.

As described in equation (15), in the processing window, only the nearest three pixels are taken into account. Actually, although the other five pixels are far from the sub-pixel $A_{5k}$ ($k = 1, 2, 3, 4$), they may still have an influence on the sub-pixel. When all pixels in the window are taken into account, equation (15) can be rewritten as:

\[
\begin{array}{|c|c|c|}
\hline
A_1 & A_2 & A_3 \\
\hline
A_4 & A_6 & \\
\hline
A_7 & A_8 & A_9 \\
\hline
\end{array}
\]

Figure 1. Sketch map of the SRQP.
where \( w_1 \) and \( w_2 \) are the weights of power \( P^i_j (j = 1, 2, \cdots, 9) \), and their values are determined by the distance between sub-pixels and original pixels. When original pixels \( A_j (j = 1, 2, \cdots, 9, j \neq 5) \) are neighbouring sub-pixel \( A_{5k} (k = 1, 2, 3, 4) \), the weight is \( w_1 \). Otherwise, the weight is \( w_2 \). Obviously, \( w_1 > w_2 \) is satisfied. As shown in figure 1, for each sub-pixel, three original pixels are neighbouring it and five original pixels are far from it. So, \( w_1 \) and \( w_2 \) are subject to the constraint \( 3w_1 + 5w_2 = 1 \). In this article, \( w_1 \) and \( w_2 \) have been set to be 0.2 and 0.08, respectively. Then, the weighted total power of all pixels in the window is defined as:

\[
P^i_1 = (w_1 + 3w_2) \left( P^i_1 + P^i_2 + P^i_7 + P^i_9 \right) + 2 (w_1 + w_2) \left( P^i_2 + P^i_4 + P^i_6 + P^i_8 \right).
\]

Therefore, the super-resolution processing of the \( i \)th scattering mechanism of \( A_5 \) is completed. We can get the super-resolved sub-pixels in the same way for other pixels.

### 3.2 Methodology of the SRPSC

The method based on quadrant pixels is straightforward and can improve the resolution of PolSAR images. However, it does not make full use of the polarimetric spatial correlation. Therefore, polarimetric spatial correlation can be used to distribute the scattering mechanism and improve the resolution of PolSAR images.

Figure 2 is the sketch map of the SRPSC. Figure 2(a) is the original low-resolution image, and the low-resolution image is decomposed by CTD using equation (1). \( A_5 \) is the central pixel, for which we have:

\[
S_5 = \sum_{i=1}^{m} c^i_5 S_5^i = c^1_5 S_5^1 + \cdots + c^5_5 S_5^5 + \cdots + c^m_5 S_5^m.
\]

![Figure 2](image.png)

Figure 2. Sketch map of the SRPSC: (a) original low-resolution image and (b) high-resolution image.
The coefficient $c_j^i$ corresponds to the weight of the $i$th scattering mechanism of $A_5$. In the following discussion in this article, we take $c_j^i$, for example, to give a detailed description of the super-resolution procedure.

At first, each low-resolution pixel is divided into four sub-pixels whose values are $1/4$ of the corresponding low-resolution pixel, and we get the initial high-resolution image, shown in figure 2(b).

Suppose $A_5$ in the red square is the resolution cell to undergo super-resolution and $A_{5k}$ ($k = 1, 2, 3, 4$) are the sub-pixels. In the high-resolution image of figure 2(b), take the sub-pixel $A_{51}$ and its $3 \times 3$ window (in the blue square) as an example. In the $3 \times 3$ processing window, the coefficients in each pixel are $c_j^i$ ($j = 1, 2, \ldots, 9; k = 1, 2, 3, 4$), where $i$ is the number of the scattering mechanism in PTD, $k$ is the index of the sub-pixel of each resolution cell and $j$ is the sequence number of the resolution cell in the processing window. The spatial correlation difference of the $i$th scattering mechanism in $A_{51}$ is defined as:

$$R_{51}^i = |c_{51}^i - c_{14}^i|^2 + |c_{51}^i - c_{23}^i|^2 + |c_{51}^i - c_{24}^i|^2 + |c_{51}^i - c_{42}^i|^2 + |c_{51}^i - c_{52}^i|^2$$

$$+ |c_{51}^i - c_{44}^i|^2 + |c_{51}^i - c_{53}^i|^2 + |c_{51}^i - c_{54}^i|^2.$$  (20)

$R_{51}^i$ can express the correlation difference of $A_{51}$ and the other sub-pixels in the $3 \times 3$ window. The less $R_{51}^i$ is, the more similar to the adjacent sub-pixels $A_{51}$ is. For the other sub-pixels $A_{52}, A_{53}$ and $A_{54}$, we can define the spatial correlation differences $R_{52}^i, R_{53}^i$ and $R_{54}^i$ in the same way:

$$R_{52}^i = |c_{52}^i - c_{23}^i|^2 + |c_{52}^i - c_{24}^i|^2 + |c_{52}^i - c_{33}^i|^2 + |c_{52}^i - c_{51}^i|^2 + |c_{52}^i - c_{61}^i|^2$$

$$+ |c_{52}^i - c_{53}^i|^2 + |c_{52}^i - c_{54}^i|^2 + |c_{52}^i - c_{63}^i|^2,$$  (21)

$$R_{53}^i = |c_{53}^i - c_{43}^i|^2 + |c_{53}^i - c_{51}^i|^2 + |c_{53}^i - c_{52}^i|^2 + |c_{53}^i - c_{44}^i|^2$$

$$+ |c_{53}^i - c_{54}^i|^2 + |c_{53}^i - c_{72}^i|^2 + |c_{53}^i - c_{81}^i|^2 + |c_{53}^i - c_{62}^i|^2$$  (22)

and

$$R_{54}^i = |c_{54}^i - c_{51}^i|^2 + |c_{54}^i - c_{52}^i|^2 + |c_{54}^i - c_{61}^i|^2 + |c_{54}^i - c_{53}^i|^2$$

$$+ |c_{54}^i - c_{63}^i|^2 + |c_{54}^i - c_{81}^i|^2 + |c_{54}^i - c_{82}^i|^2 + |c_{54}^i - c_{91}^i|^2.$$  (23)

The total spatial correlation difference of the four sub-pixels is the sum of $R_{5i}^i$:

$$R_5^i = R_{51}^i + R_{52}^i + R_{53}^i + R_{54}^i.$$  (24)

$R_5^i$ denotes the similarity between the four sub-pixels and their adjacent pixels. As we know, the four sub-pixels $A_{5k}$ ($k = 1, 2, 3, 4$) are derived from the low-resolution pixel $A_5$, and they must satisfy the relationship:

$$c_{51}^i + c_{52}^i + c_{53}^i + c_{54}^i = c_5^i.$$  (25)

Therefore, the problem is to calculate the optimal value $c_{5k}^i$ of $c_{5k}^i$ ($k = 1, 2, 3, 4$) so as to minimize equation (24) constrained by equation (25):
\[ c_{5k}^+ = \arg \min_{c_{5k}(k=1,2,3,4)} (R_5) \text{ subject to } c_{51}^i + c_{52}^i + c_{53}^i + c_{54}^i = c_5^i. \]  \hspace*{1cm} (26)

The conditional extremum of equation (26) can be solved using the Lagrange multiplier (\( \lambda \)):

\[ R_5^i + \lambda (c_{51}^i + c_{52}^i + c_{53}^i + c_{54}^i - c_5^i) = 0. \]  \hspace*{1cm} (27)

Theoretically, the optimal value \( c_{5k}^i \) \( (k = 1, 2, 3, 4) \) and \( \lambda \) could be obtained through the partial derivative of equation (27) with respect to \( c_{5k}^i \) \( (k = 1, 2, 3, 4) \) under the constraint of equation (25).

### 3.3 Solution procedure of the SRPSC

A complex function \( f(z) = |z|^2 \) (where \( Z \) is complex) cannot be derived, except at point \( (0, 0) \). Therefore, the solution cannot be obtained directly. From a mathematical point of view, \( f(z) = |z|^2 \) can be expressed as:

\[ f(z) = |z|^2 = |x + jy|^2 = x^2 + y^2 = f(x, y), \]  \hspace*{1cm} (28)

where \( z = x + jy \) is complex. \( f(z) = f(x, y) \) is a function of \( x \) and \( y \) and it is a derivative. Accordingly, the constraint equation (25) can be rewritten as:

\[ \left\{ \begin{array}{l}
    c_{51R} + c_{52R} + c_{53R} + c_{54R} = c_{5R}, \\
    c_{51I} + c_{52I} + c_{53I} + c_{54I} = c_{5I},
\end{array} \right. \]  \hspace*{1cm} (29)

where \( R \) and \( I \) represent real and imaginary parts, respectively.

The conditional minimum of \( R_5 \) constrained by equation (29) can be solved by the Lagrange multiplier:

\[ R_5 + \lambda_1 (c_{51R} + c_{52R} + c_{53R} + c_{54R} - c_{5R}) + \lambda_2 (c_{51I} + c_{52I} + c_{53I} + c_{54I} - c_{5I}) = 0. \]  \hspace*{1cm} (30)

\( \lambda_1, \lambda_2, c_{5kR} \) and \( c_{5kI}(k = 1, 2, 3, 4) \) can be obtained through the partial derivative of equation (30) with respect to \( c_{5kR} \) and \( c_{5kI} \) \( (k = 1, 2, 3, 4) \) under the constraint of equation (29):

\[ \left\{ \begin{array}{l}
    \lambda_1 = \frac{1}{2} (\beta_{1R} + \beta_{2R} + \beta_{3R} + \beta_{4R} - 5c_{5R}), \\
    \lambda_2 = \frac{1}{2} (\beta_{1I} + \beta_{2I} + \beta_{3I} + \beta_{4I} - 5c_{5I}), \\
    c_{5kR} = \frac{1}{13} (2c_{5R} + \beta_{kR} - \frac{1}{2} \lambda_1), \\
    c_{5kI} = \frac{1}{13} (2c_{5I} + \beta_{kI} - \frac{1}{2} \lambda_2),
\end{array} \right. \]  \hspace*{1cm} (31)

where \( \beta_k \) \( (k = 1, 2, 3, 4) \) is the sum of the sub-pixels, except \( c_{51}, c_{52}, c_{53}, c_{54} \) in the \( 3 \times 3 \) window of \( c_{5k} \).

Therefore, the coefficient \( c_{5k} \) \( (k = 1, 2, 3, 4) \) of each sub-pixel can be derived using:

\[ c_{5k} = c_{5kR} + j c_{5kI} \quad (k = 1, 2, 3, 4). \]  \hspace*{1cm} (32)
By combining equations (20)–(32), we get a super-resolution image from the original high-resolution image, and the spatial correlation and resolution are both improved.

The same procedure can be implemented iteratively and the root mean square error (RMSE) of the images in the $n$th and the $(n+1)$th iteration can be defined as the termination condition. The RMSE is defined as:

$$ e = \sqrt{\frac{1}{MN} \sum_{0 \leq i \leq M} \sum_{0 \leq j \leq N} (f_{ij}^{n+1} - f_{ij}^n)^2}, $$

where $(i, j)$ denotes the position of the pixel, $f_{ij}^n$ and $f_{ij}^{n+1}$ are the values of the pixels of $I_n$ and $I_{n+1}$, $I_n$ and $I_{n+1}$ are the images of the $n$th and the $(n+1)$th iteration, respectively. $M$ and $N$ are the number of rows and columns of the image, respectively. In the iteration process, if $e < \varepsilon$ ($\varepsilon$ is a given constant), the iteration stops.

Figure 3 shows the flow chart of the SRPSC, and a summary of the iterative SRPSC is described by the following:

1. obtain the spatial correlation differences of each component by PTD;
2. set initial RMSE, $e = 1000$, and condition of iteration termination, $\varepsilon = 0.01$, or maximum number of iterations, $n_{\text{max}} = 20$. For the $i$th component, begin at $n = 0$ with initial high-resolution image $I_0$;
3. in the $n$th iteration, according to each low-resolution pixel and corresponding four high-resolution sub-pixels, calculate $c_{ij}$ according to equation (26), and then the high-resolution image $I_{n+1}$ is obtained;
4. if the RMSE, $e$, of $I_n$ and $I_{n+1}$ is less than $\varepsilon$ or iteration number, $n$, reaches $n_{\text{max}}$, then the iteration process stops;
5. otherwise, set $n = n + 1$ and return to step 3;
step 6: for the other components, implement steps 2–5;
step 7: get the super-resolution image.

3.4 Evaluation criterion of the SRPSC

The evaluation of the performance of the super-resolution method is an important procedure in the image reconstruction. If the high-resolution image exists, the RMSE, relative error, SNR or peak SNR of the real image and the reconstructed image can be calculated. However, it is very difficult to obtain the high-resolution image to evaluate the performance of the super-resolution method. We can adopt indirect approaches to evaluate the performance of reconstruction. Generally, the evaluation is validated using the low-resolution image, which is synthesized by real SAR images or standard test images.

The low-resolution image is obtained by adding the adjacent four pixels for the hh, hv, vh and vv channels. The sketch map of the degraded model for evaluation is shown in figure 4. The adjacent four pixels in the original image are added to form a new low-resolution pixel. In SAR images, a pixel value represents the complex backscattering coefficient in a resolution cell. If the resolution is relatively low, the backscattering powers of the adjacent area will be overlapped in a low-resolution cell. Therefore, the degraded model in figure 4 is reasonable in SAR processing. So, a test image, composed of 200 × 200 pixels, can be degraded to 100 × 100 pixels for the low-resolution image, and the original image is considered to be the high-resolution image. Then, the super-resolution method is implemented to the degraded image and the evaluation of the super-resolution image and the original image is validated.

In this article, we use the RMSE to evaluate the performance of the SRPSC. The expression of RMSE is given by:

\[
e = \sqrt{\frac{1}{MN} \sum_{0 \leq i \leq M} \sum_{0 \leq j \leq N} (f_{ij} - \hat{f}_{ij})^2},
\]

where \(f_{ij}\) and \(\hat{f}_{ij}\) are the values of the pixels in the original image and the reconstructed image, respectively. \(M\) and \(N\) are the number of rows and columns of the image, respectively.

The RMSE is a common appreciation criterion of image quality. It is better to calculate the difference of images and quantize the error. The smaller the RMSE is, the more similar the reconstructed and original images. However, the RMSE does not

![Figure 4. Sketch map of degraded model for evaluation: (a) original image and (b) degraded image.](image-url)
agree with the subjective visual impression. This is because the RMSE is a global estimation and it does not reflect local features, especially some features detected by the human eye.

4. Experimental results and discussion

The proposed SRPSC in this article is verified by using the German Aerospace Center (DLR) Experimental SAR (E-SAR) L-band full polarized images of the Oberpfaffenhofen Test Site Area in Germany. Its spatial resolution is $3 \times 3$ m. Figure 5 shows the test data of Oberpfaffenhofen Test Site Area (DE) in Germany. Figure 5(a) is the amplitude image of the hh channel image of the E-SAR data. We zoomed-in on a small urban area of $200 \times 200$ pixels (shown by the red square in figure 5(a)) to give detailed information. Figure 5(b) is the zoomed-in image of the urban area of $200 \times 200$ pixels. The optical image of the urban area is given in figure 5(c) to show the ground truth.

Figure 6(a) shows the result of Pauli decomposition of the original image of urban area. The image is coloured by $\alpha$ (red), $\beta$ (green) and $\gamma$ (blue). Figure 6(b) gives the super-resolution image of an urban area of $400 \times 400$ pixels using the SRPSC. As shown in figure 6, we find that the SRPSC gives a better super-resolution result. The whole image becomes more legible, and some isolated pixels become more distinct; at the same time, the polarization properties of the targets are preserved and undesirable oscillation effects, causing spurious peaks, are avoided.

In order to give a quantitative estimation of the SRPSC, the degraded images of four polarimetric channels are firstly formed based on the degraded model (shown in figure 4). Then three scattering components (single bounce, double bounce and $45^\circ$ rotated double bounce) are obtained by polarimetric decomposition. The degraded low-resolution pseudocolour image of Pauli decomposition is shown in figure 7(a). Subsequently, the super-resolution method is employed for the three scattering components, respectively. Figure 7(b) shows the super-resolution image of the SRPSC. In this experiment, the super-resolution image is expanded back to $200 \times 200$ pixels. Figure 7(c) is the original image of $200 \times 200$ pixels, which is considered to be the

Figure 5. The test data of Oberpfaffenhofen Test Site Area (DE) of Germany: (a) hh channel image of the E-SAR data, (b) zoomed-in image of the urban area of $200 \times 200$ pixels in the red square in (a) and (c) optical image of the urban area.
Figure 6. Super-resolution of urban area based on Pauli decomposition: (a) original image of the urban area of 200 × 200 pixels and (b) super-resolution images of 400 × 400 pixels based on SRPSC.

Figure 7. Quantitative comparison of the result of the SRPSC based on Pauli decomposition: (a) degraded low-resolution image of 100 × 100 pixels, (b) super-resolution image of 200 × 200 pixels and (c) original image of 200 × 200 pixels (considered as the high-resolution image).

high-resolution image. Finally, the comparison of the super-resolution image and original image of each scattering component is implemented, and the RMSE is calculated to evaluate the performance of the proposed super-resolution method. Figure 8 shows the relationship of logarithmic RMSE and iteration time. The RMSE can evidently drop when iteration increases, and 12 iterations of the SRPSC will get the relative high super-resolution images.
To give a qualitative comparison, we compare the results of the SRPSC with those of the SRQP. Figure 9 gives the $200 \times 200$ pixels super-resolution images of the urban area using the SRQP and SRPSC, (a) is the degraded image of $100 \times 100$ pixels, (b) is the result of the SRQP, while (c) is the result of the SRPSC. It is obvious that the super-resolution images obtained by the SRQP and SRPSC are quite different. From figure 9, we can find that the SRPSC gives a better super-resolution result. For the SRQP, although the resolution of the image is somewhat improved, the estimated positions and polarization properties of the targets are less accurate and, furthermore, undesirable oscillation effects, causing spurious peaks, can be found. Whereas, for the SRPSC, the whole image becomes more legible, and some isolated pixels become more distinct; at the same time, polarization properties of the targets are preserved and undesirable oscillation effects, causing spurious peaks, are avoided. Table 1 gives the RMSEs of the SRQP and SRPSC for the $\alpha$, $\beta$ and $\gamma$ components of Pauli decomposition. From table 1, we can see that the average RMSEs of the SRQP and SRPSC are 8.08 and 7.86, respectively. The results indicate that the super-resolution image of the SRPSC is closer to the original image. In fact, although the SRQP improves the...
resolution of the PolSAR image, it does not make full use of the polarimetric spatial correlation, so many spurious peaks appear.

Similar results of the SRQP and SRPSC can be obtained using SDH decomposition, Freeman decomposition and OEC decomposition. Figures 10, 11 and 12 show the results of the SRQP and SRPSC using SDH decomposition, Freeman decomposition and OEC decomposition, respectively. The colour is based on the SDH representation of the scattering matrix where red, green and blue represent the magnitude of each component $k_s$, $k_d$ and $k_h$, respectively. Table 2 gives the RMSEs of the SRQP and SRPSC for SDH decomposition. The average RMSEs of the SRQP and SRPSC are 4.45 and 4.10, respectively. The results show again that the SRPSC is better than the SRQP. The results of the Freeman decomposition are coloured $f_{\text{double}}$

<table>
<thead>
<tr>
<th></th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>$\gamma$</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRQP</td>
<td>8.31</td>
<td>10.51</td>
<td>5.42</td>
<td>8.08</td>
</tr>
<tr>
<td>SRPSC</td>
<td>7.71</td>
<td>10.70</td>
<td>5.17</td>
<td>7.86</td>
</tr>
</tbody>
</table>

Figure 10. Comparison of the results based on SDH decomposition: (a) degraded low-resolution image of 100 × 100 pixels, (b) 200 × 200 pixels super-resolution image of the SRQP and (c) 200 × 200 pixels super-resolution image of the SRPSC.

Figure 11. Comparison of the results based on Freeman decomposition: (a) degraded low-resolution image of 100 × 100 pixels, (b) 200 × 200 pixels super-resolution image of the SRQP and (c) 200 × 200 pixels super-resolution image of the SRPSC.
Super-resolution of PolSAR images

Figure 12. Comparison of the results based on OEC decomposition: (a) degraded low-resolution image of $100 \times 100$ pixels, (b) $200 \times 200$ pixels super-resolution image of the SRQP and (c) $200 \times 200$ pixels super-resolution image of the SRPSC.

Table 2. The RMSE of the SRQP and the SRPSC for SDH decomposition.

<table>
<thead>
<tr>
<th></th>
<th>$k_s$</th>
<th>$k_d$</th>
<th>$k_h$</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>SRQP</td>
<td>5.39</td>
<td>5.65</td>
<td>5.67</td>
<td>5.56</td>
</tr>
<tr>
<td>SRPSC</td>
<td>4.11</td>
<td>4.70</td>
<td>4.84</td>
<td>4.55</td>
</tr>
</tbody>
</table>

(red), $f_{\text{volume}}$ (green) and $f_{\text{surface}}$ (blue), whereas the results of the OEC decomposition are coloured $f_{\text{even}}$ (red), $f_{\text{odd}}$ (green) and $f_{\text{cross}}$ (blue). All the results confirm that the SRPSC has a good performance in PolSAR image super-resolution.

5. Conclusion

In this article, we have proposed a novel super-resolution algorithm for PolSAR images depending on PTD and polarimetric spatial correlation. The predominant advantage of the super-resolution method is that the phase information is preserved for PolSAR images. Furthermore, the super-resolution images of CTD can be extended into the incoherent decomposition methods for further research. The experiments are implemented using E-SAR L-band full polarized images. The results show that the SRPSC can give a better super-resolution result, because the SRPSC makes full use of the polarimetric spatial correlation. The positions and the polarization properties of the target are well restored, the whole image becomes more legible and some isolated pixels become more distinct. To give a quantitative analysis, in the experiment, the pixels of the PolSAR image are reduced to half of the original image in both range and azimuth directions and expanded back to the original pixels by the super-resolution algorithms. With the quantitative measure, i.e. RMSE, results shows that the image obtained by the SRPSC is close to the original image.

Acknowledgements

This work was supported by National Natural Science Foundation of China (No.60672091 and No.60872098) and the Postdoctoral Science Foundation of China (No. 20100481009).


