Monitoring Broadleaf Forest Pest Based on L-Band SAR Tomography

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Abstract. Synthetic aperture radar tomography (TomoSAR) has been proved to be able to reconstruct 3D reflectance of volumetric targets, such as vegetation. It gives us an opportunity and a possibility to monitor forest pest through extracting 3D structural information of the forest. In this paper, TomoSAR echo data of normal and pest forest are simulated with PolSAR Pro at L-band before and after the pest respectively, after analysing physical geometry and backscattering properties of forest pest and disease. Then, a method used for extracting 3D structure information of the forest is presented and discussed. Finally, differences between the normal and pest forest are demonstrated and analyzed with the TomoSAR imaging results.

1. Introduction
Forest pests and diseases are one of the major forest disasters in China and their damage is extremely serious. Effective monitoring and forecasting of pests and diseases is an important part of controlling the spread of pests and diseases, maintaining forest health and sustainable development.

Hyperspectral remote sensing and microwave imaging are main frontiers of modern remote sensing monitoring technology and the use of hyper spectral remote sensing technology for forest pest monitoring has achieved certain results. Synthetic Aperture Radar (SAR) provides higher sensitivity to vertical alignment of forest elements, due to the ability to penetrate vegetation layers and interact with forest structures[1-3]. It has incomparable advantages of other passive optical remote sensing methods of monitoring the relevant parameters of forest vegetation (canopy height, biomass, etc.)(4]. SAR not influenced by clouds and rain, also has all-weather, all-time advantage of monitoring[5]. In the past 20 years, many forest vegetations scattering models and physical parameter estimation algorithms have been proposed based on SAR, but they have not been applied to forest pest monitoring[6]. Therefore, how to use SAR for forest pest monitoring is still at the forefront of remote sensing technology.

The Tomography Synthetic Aperture Radar (TomoSAR) technology is an emerging cutting-edge technology developed in the past decade to acquire multiple SAR images of different viewing angles in the same scene to obtain high-precision 3D and 4D information. It can measure the
height-distributed scatters by changing the image processing algorithm after imaging[7]. TomoSAR has strong detection capability for ground target spatial structure and terrain, especially for the detection of vertical structures of ground targets, and has the advantage that other remote sensing data cannot match[8].

Based on this, this paper carried out the following researches: (1) Studied the physical geometry of pests and forests in the absence of trees, and then simulated the multi-baseline SAR data for the physical and physical forest areas. (2) SAR tomographic inversion model and method for the obtained simulated SAR data, extracted the three-dimensional structure information of the forest. (3) Compared the three-dimensional structure information of the forest under different conditions, analyzed the differences, and finally established forest pest and disease monitoring model and method based on TomoSAR.

2. Methodology

2.1 Tomographic SAR Model

Through multiple baseline synthetic aperture radar (SAR) observations over the same area at different times and slightly different orbit positions (the elevation aperture), a stack of N complex SAR datasets can be obtained. Each perpendicular baseline with respect to a master track can be calculated. After some preparation of the stack of data (registration and phase compensation, for example), the focused complex value of an azimuth-range pixel of the nth acquisition is:

\[ g_n = \int_{s} y(s) \exp(-j2\pi \xi_n s) ds \]  

(1)

where \( y(s) \) represents the reflectivity function along elevations \( s \) and \( \Delta s \) describes the range elevations. \( \xi_n = -2b_n/(\lambda r_0) \) is the spatial (elevation) frequency depending on the (more or less random) elevation aperture position \( b_n \), range \( r_0 \) and the wavelength \( \lambda \). We can see from the continuous-space system model of (1) that the multi-baseline data acquisition is actually a randomly sampled Fourier transform of \( y(s) \). Thus, an inherent Rayleigh resolution in elevation is \( \rho_e = \lambda r/(2\Delta b) \), where \( \Delta b \) is the elevation aperture size. Through approximation by discretizing the continuous reflectivity function along \( s \), in the presence of noise \( \varepsilon \), the discrete reflectivity function-space system model can be written as:

\[ g = A\gamma + \varepsilon \]  

(2)

where \( g \) is the measurement vector with N elements \( g_n \), \( A = [a_1, a_2, ..., a_L] \) is an N × L mapping matrix with \( A_{nl} = \exp(-j2\pi s_l) \) in which \( s_l \) (\( l = 1, \ldots, L \)) denotes L discrete elevation positions, and \( \gamma \) is the discrete reflectivity vector with L elements \( \gamma_l = y(s_l) \). Equation (2) is a sampled discrete Fourier transform of the elevation profile \( y(s) \).

2.2 Beamforming method

After multi-baseline SAR data acquisition and data preprocessing, for a given distance and azimuth pixel, we obtain a random signal vector of length M: \( g = (g_1, g_2, ..., g_M)^T \). Not general, assuming that these data are zero-averaged. We directly inverse-Fourier transform the data in the M spatial frequency domain to obtain the spectral information at the height position \( s_n \) of the spatial domain \( \hat{y}(s_n) \):

\[ \hat{y}(s_n) = r(s_n)^H g \]  

(3)

The product of the spectrum and its conjugate is then obtained to obtain the power spectrum at the height position \( s_n \).

\[ P_{\hat{y}}(s_n) = \frac{1}{M} |\hat{y}(s_n)|^2 = \frac{1}{M} |r(s_n)^H g|^2 \]  

(4)

The above method is a single view beamforming method that utilizes only multiple baseline information to one pixel.

In order to improve the signal-to-noise ratio, we often need to use the statistical characteristics of random signals to analyze and process them. This requires us to perform multi-view processing on SAR images. In the actual processing of tomographic SAR, we use the central pixel and surrounding
pixels of the same type to achieve independent and identically distributed L-view processing for each SAR image. After multi-view processing, the formula $g = \sum_{n=1}^{N} y_n r(s_n) + \varepsilon$ shows that the random signal vector obtained by multi-baseline SAR can be expressed as:

$$g(l) = \sum_{n=1}^{N} y_n(l) r(s_n) + \varepsilon(l), l = 1, 2, \ldots, L$$

(5)

Where $l$ represents looks.

We know that the second-order statistic self-covariance function of random signals and its power spectral density are Fourier transforms, so we can estimate the power spectrum information based on the auto-covariance matrix $C_{gg}$ of the random signal vector obtained by multi-baseline SAR. It should be pointed out that: In the foregoing, we have assumed that the data is zero-melanized, then the autocorrelation matrix of the random signal sequence is equivalent to the covariance, so we can use the autocorrelation matrix of the random signal sequence to represent its autocovariance matrix. In the actual processing, we approximate the autocorrelation matrix by using the sample autocorrelation matrix of the random signal vector obtained by multi-baseline SAR.

$$\hat{C}_{gg} = \frac{1}{L} \sum_{l=1}^{L} g(l) g(l)^H$$

(6)

The power spectrum estimate for the multi-view beamforming method can then be defined as:

$$\hat{P}_B(s_n) = \frac{r(s_n)^H \hat{C}_{gg} r(s_n)}{M^2}$$

(7)

3. Experiments

Based on the tomographic SAR system and simulation scenario parameters provided in Table 1, the full-polarization tomographic SAR data can be calculated using PolSAR pro simulation software developed by ESA. The experiment uses a simulated airborne SAR platform. The L-band has better penetration ability and can collect more information on forest institutions. The platform height is set at an altitude of 3000 meters. Each group of experiments collects twelve baselines. The elevation to synthetic aperture length is 164.07 meters, the azimuth resolution is set to 1.5 meters and the range resolution is set to 1.0607 meters.

| Table 1. Baseline parameters |
|-----------------------------|
| Main image                  | 0m       |
| Secondary image 1           | 25.67m   |
| Secondary image 2           | 43.33m   |
| Secondary image 3           | 57.28m   |
| Secondary image 4           | 68.14m   |
| Secondary image 5           | 79.03m   |
| Secondary image 6           | 91.76m   |
| Secondary image 7           | 104.10m  |
| Secondary image 8           | 115.85m  |
| Secondary image 9           | 128.21m  |
| Secondary image 10          | 143.07m  |
The simulated natural scene set in this experiment is a deciduous forest with 300 trees. The tree height is 21 m, the planting density is about 300 trees/ha, and the total area is 10,000 square meters (1 hectare). We represent a normal deciduous forest with a forest with a sparsity of 90, and a forest with a sparseness of 0.1 represents a defoliated forest with severe leaf loss. In order to maintain the principle of contrast and single variable, the random number is set to 0 for each simulation, the azimuth and distance are set to 0 to the ground slope, the ground is set to be the smoothest, and the moisture content is set to 0.

We separately interfered and de-slanted the main image and the auxiliary image of the two sets of simulation data to obtain pre-processed images that can be used for tomographic SAR imaging. Next, we used the beamforming method to perform three-dimensional imaging of the tomographic SAR, and the two images are vertically sliced at the position indicated by the red line in Fig. 2(a) to obtain two images of Figs. 2(b) and (c).

![Figure 1. Example of deciduous tree model used in the text.](image)

![Figure 2. Profile area tomographic SAR spectrum information](image)

(The picture (a) is a SAR image of a simulated forest, the red line in the figure is represented as a vertical section position. The picture (b) shows the forest of normal deciduous forest and the picture (c) shows the forest of leafless deciduous forest)

4. Conclusion

Comparing the cross-sectional tomographic SAR spectrum information of the two forests, it can be found that the backscattering information of the ground and the canopy can be clearly observed in the normal deciduous forest, while the lost-leaf forest can only see the backscattering information of the ground. This is due to the fact that the canopy with leaves forms a strong backscattering center. Based on this obvious contrast, the leafless inversion of the forest area can be achieved.

The vertical distribution of backscatter power can be obtained by means of chromatography, and the profile information that can indicate the vertical structure of the forest can be obtained. By defining corresponding characteristics according to the profile shape of the vertical structure, it can not only be used to extract the sub forest topography and forest tree height, but also can be used to estimate the above-ground biomass of the forest. How to further explore its value in estimation of forest vertical structure parameters is still a key problem that needs further study. In general,
tomographic technology further expands the theory and method of multi-dimensional SAR in the application field of remote sensing monitoring, which is of great significance for quantitative estimation of forest vertical structure parameters.

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