Speckle Denoising for Synthetic Aperture Radar Images Based on Genetic Algorithm and 2D Dual-Tree Complex Wavelet Transform (2D-DT-CWT)

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Abstract

Synthetic aperture radar (SAR) images are an important tool for obtaining target information in remote sensing. Synthetic aperture radar (SAR) images are inherently affected by multiplicative speckle noise, which is due to the coherent nature of the scattering phenomenon. It appears sensible to reduce speckle in SAR images, provided that the structural features and textural information are not lost.

Present A novel speckle removal algorithm is presented by using Dual-Tree Complex Wavelet Transform (2D-DT-CWT) and Genetic algorithm (GA). In the proposed model, Genetic algorithm based on 2D Dual-Tree Complex Wavelet Transform is introduced into the method of noise reduction where parameters used in Dual-Tree Complex Wavelet Transform, such as, decomposition levels, hard or soft threshold and threshold value can be selected automatically. Simulation results show that by using proposed method, obtain higher Peak Signal to Noise Ratio (PSNR) comparing with classical wavelet transform for all the denoised SAR images with speckle noise. The effectiveness of proposed method introduced in this paper is validated by the results of analysis of the simulated.

Keywords: Speckle Noise, SAR image, Genetic Algorithm and Complex Wavelet Transform

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الخلاصة

صور رادار الفتحة الصناعي (SAR) أداة مهمة للحصول على معلومات عن الهدف عن بعد. صور رادار الفتحة الصناعي تتأثر بضوضاء النقط وهو نتيجة للطبيعة المتماسكة لظاهرة التبعثر. عند إزالة ضوضاء النقط يجب إن لا نخسر المعلومات الموجودة في صور SAR . في هذا البحث اقترح طريقة لإزالة ضوضاء النقط باستخدام الجينة الوراثية (GA) المحول المويجي المركب ثنائي الإبعاد ذي الشجرة الثنائية (2D-DT-CWT). في هذا النموذج المقترح لإزالة ضوضاء النقط , الجينات الوراثية تستطيع اختيار العناصر التي تستخدم في محول المويجي المركب ثنائي الإبعاد ذي الشجرة الثنائية مثل (عدد مستويات التحليل و قيمة العتبة و عتبة hard او soft) بصورة تلقائية. محصلة نتائج المحاكة بينت إن النموذج المقترح يستطيع الحصول على نسبة عالية لنسبة قمة الإشارة إلى الضوضاء (PSNR) بالمقارنة مع الطرق الاعتيادية لإزالة ضوضاء النقط في صور SAR وكذلك تبين ان النموذج المقترح ذو فعالية عالية

1. Introduction

A synthetic aperture radar (SAR), is a coherent radar system that generates high resolution remote sensing imagery, using a synthetic antenna installed aboard aircraft or spacecraft. Unlike conventional radar, SAR uses the platform movement to obtain a larger synthetic antenna, with finer azimuth resolution than the real antenna. During the data acquisition process, the target is illuminated by the antenna beam from different positions along its trajectory, resulting a relatively long synthetic aperture, which yields finer resolution than is possible from a smaller physical antenna. High-resolution synthetic aperture radar is a very effective terrain and sea surface mapping tool. However, SAR imagery is degraded by a form of multiplicative noise known as speck [1,2].

Hence, speckle reduction is a necessary procedure before automatic image analysis can be performed [3]. The application of wavelets to signal and image compression and to denoising is well researched. Orthogonal wavelet decompositions, based on separable, multirate filtering systems have been widely used in image and signal processing, largely for image denoising. Kingsbury introduced a very elegant computational structure, the dual - tree complex wavelet transform [4], which displays near-shift invariant properties. Complex wavelets have not been used widely in image processing due to the difficulty in designing complex filters which satisfy a perfect reconstruction property.

To overcome this, Kingsbury proposed a dual-tree implementation of the CWT (DT CWT) [5], which uses two trees of real filters to generate the real and imaginary parts of the wavelet coefficients separately. Genetic Algorithm (GA) is a global probability search algorithm [6], which emulates the biological evolution process of Darwin's genetic selection and natural elimination. It possesses self-adaptability, global optimization, and implicit parallelism, manifesting the strong capability in solving problems [7]. At present, combining genetic algorithm and Dual-Tree Complex Wavelet Transform to make full use of their advantages is an active research field. In this paper, based on genetic algorithm and Dual-Tree Complex Wavelet Transform anew system is proposed to Speckle Denoising for Synthetic Aperture Radar Images

2. Speckle Noise in SAR Image

SAR is a coherent imaging technology that records both the amplitude and the phase of the back-scattered radiation. An important feature that degrades SAR images quality is speckle noise, Speckle is a common noise-liken phenomenon in all coherent imaging systems. Each resolution cell of the system contains many scatterers, the phases of the return signals from these scatterers are randomly distributed and speckle is due to the coherent nature of the sensor and the signal processing. The speckle noises will appear as bright or dark dots on the image and leads to limitation on the accuracy of the measurements given that the brightness of a pixel is determined not only by properties of the scatterers in the resolution cell, but also by the phase relationships between the returns from those scatterers.

Speckle noise is multiplicative in nature [1], therefore speckle reduction techniques is essential before procedures such as automatic target detection and recognition, thus traditional filtering will not remove it easily. Speckle noise prevents automatically target recognition (ATR) and texture analysis algorithm to perform efficiently and gives the image a grainy appearance. Hence, speckle filtering turns out to be a critical pre-processing step for detection or classification optimization. There has been considerable interest in using the wavelet transform as a powerful tool for recovering images from noisy data[8]. Wavelet denoising procedures consist of three main steps: First, Calculate the wavelet transform of the noisy image. Second, Manipulating the wavelet coefficients. Third, Compute the inverse transform using the modified coefficients.

3. Complex Wavelets

The complex wavelet transform (CWT) is a combination of two real-valued DWTs. The ordinary DWT is shift variant because of the decimation operation exploited in the transform. As a result, a small shift in the input signal can cause a very different set of wavelet coefficients produced at the output. For that, Kingsbury [9] introduced a new kind of wavelet transform, called the DT-CWT or CWT, for short, which exhibits approximate shift invariant property and improves directional resolution when compared with that of the DWT. At each scale, the DT-CWT produces six directional subbands, oriented at $\pm 15^{o}$, $\pm 45^{o}$, and $\pm 75^{o}$ [10], while the DWT produces only three directional subbands, oriented at 0^{o}, 45^{o}, and 90^{o}. The DT-CWT also yields perfect reconstruction by using two parallel decimated filter-bank trees with real-valued coefficients generated at each tree. The 1-D DT-CWT decomposes the input signal $f(x)$ by expressing it in terms of a complex shifted and dilated mother wavelet $\psi(x)$ and scaling function $\varphi(x)$, i.e.[10],

$$f(x) = \sum_{l} s_{jo,l}\phi_{jo,l}(x) + \sum_{j \geq jo}\sum_{l \in Z} c_{j,l}\psi_{j,l}(x) \tag{1}$$

where Z is the set of natural numbers, j and l refer to the index of shifts and dilations, respectively, $s_{jo,l}$ is the scaling coefficient, and $c_{j,l}$ is the complex wavelet coefficient with $\phi_{jo,l}(x) = \phi^{r}_{jo,l}(x) + \sqrt{-1}\phi^{i}_{jo,l}(x)$ and $\psi_{j,l}(x) = \psi^{r}_{j,l}(x) + \sqrt{-1}\psi^{i}_{j,l}(x)$,where the superscripts r and i denote the real and imaginary parts, respectively. In the 1-D DT-CWT case, the set $\{\phi^{r}_{jo,l}, \phi^{i}_{jo,l}, \psi^{r}_{jo,l}, \psi^{i}_{jo,l}\}$ forms a tight wavelet frame with double redundancy. The real and imaginary parts of the 1-D DT-CWT are computed using separate filter banks with filters h_0 and h_1 for the real part, and g_0 and g_1 for the imaginary part, as shown in Fig. 1. The outputs from the two trees in Fig. 1 are interpreted as the real and the imaginary parts of the complex coefficients.

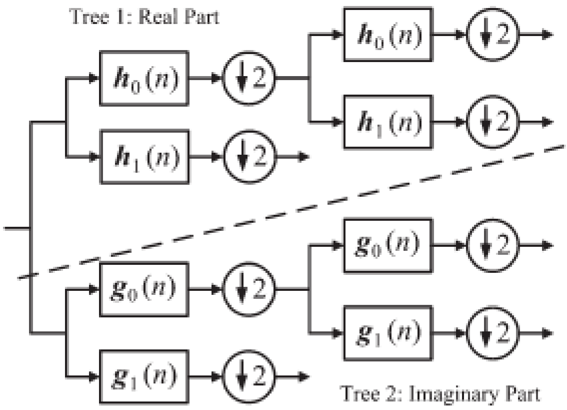


Fig. 1. Two-level 1-D DT-CWT.

Similar to the 1-D DT-CWT, the 2-D DT-CWT decomposes a 2-D image *f(x,y)* through a series of dilations and translations of a complex scaling function and six complex wavelet functions $\psi^{\theta}_{j,l}$,i.e.[10],

$$f(x,y)=\sum_{l\in Z^2} s_{jo,l}\phi_{jo,l}(x,y)+\sum_{\theta\in\Theta}\sum_{j\geq jo}\sum_{l\in Z^2} c^{\theta}_{j,l}\psi^{\theta}_{j,l}(x,y) \qquad (2)$$

where $\theta \in \Theta = \{\pm 15^o, \pm 45^o, \pm 75^o\}$ provides the directionality of the complex wavelet function.

That is, the decomposition of *f(x,y)* by exploiting the DT-CWT produces one complex valued low-pass subband and six complex-valued high-pass subbands at each level of decomposition, where each high-pass subband corresponds to one unique direction θ. DT- CWT is used for analyzing images, and has been used in some fields of image/vedio processing, such as image/vedio denoising, image segmentation, pattern recognition, and facial feature extraction. The impulse responses of the six complex wavelets of the 2-D CWT are shown in Fig. 2 [11]. The frequency-domain partition resulted from a two-level 2-D DT-CWT decomposition is graphically shown in Fig. 3

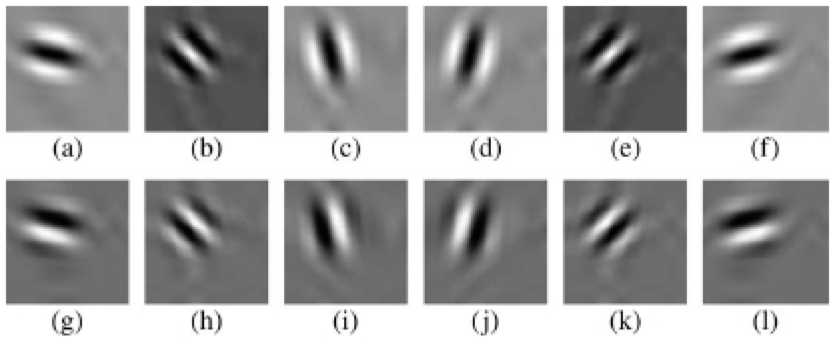


Fig. 2. Real (R) and imaginary (I) parts of the impulse responses of the 2-D DT-CWT filters under six directional subbands: (a) $R_{-15}{}^o$, (b) $R_{-45}{}^o$, (c) $R_{-75}{}^o$, (d) $R_{+75}{}^o$, (e) $R_{+45}{}^o$, (f) $R_{+15}{}^o$, (g) $I_{-15}{}^o$, (h) $I_{-45}{}^o$,(i) $I_{-75}{}^o$, (j) $I_{+75}{}^o$, and (k) $I_{+45}{}^o$, and (l) $I_{+15}{}^o$.

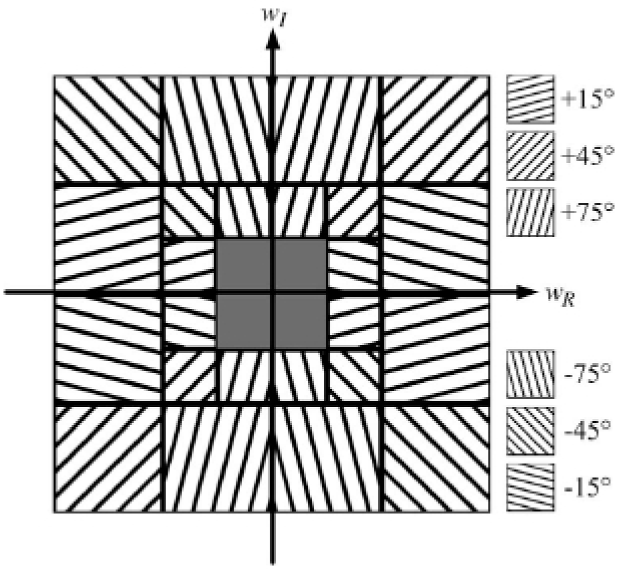


Fig. 3. Frequency-domain partition resulted from a two-level 2-D DT-CWT decomposition, where w_R and w_I are the real axis and the imaginary axis of the complex frequency domain, respectively

4. Genetic Algorithm

Conventional search techniques are often incapable of optimizing nonlinear functions with multiple variables. One scheme called the "genetic algorithm" (GA) [12], based on the concept of natural genetics, is a directed random search technique developed in 1975. In the GA, parameters are represented by an encoded binary string, called the chromosome. The elements (or bits) in the binary strings, or the genes, are adjusted to minimize or maximize the fitness value. The fitness function generates its fitness value, which is composed of multiple variables to be optimized by the GA. For every iteration in the GA, a pre-determined number of individuals will correspondingly produce fitness values associated with the chromosomes. The GA begins by defining the optimization parameters, the fitness function, and consequently the fitness value, and it ends by testing for convergence. Three major building blocks in the GA include selection, crossover, and mutation. They are briefly described as follows:

- Selection: In the training process, a large portion of the low fitness individuals is discarded through this natural selection step.

- Crossover: Two individuals are chosen from the mating pool of N good individuals, meaning those with larger fitness values or those with a better chance for survival, to produce two new offspring. A crossover point is selected between the first and last chromosomes of the parent individuals. Then the fraction of each individual after the crossover point is exchanged and concatenated.

- Mutation: This step can introduce traits not found in the original individuals and keeps the GA from converging too fast. The simplest way to do this is intentionally flip some randomly selected bits in the chromosome. Generally speaking, by following the findings in genetics, the probability for mutation is supposed to be low.

Figure 4 shows the flow chart of GA. According to the applications for optimization, designers need to carefully define the necessary elements for training with the GA. Then, the fitness function in addition to the terminating criteria is evaluated with the natural selection, crossover, and mutation operations [13].

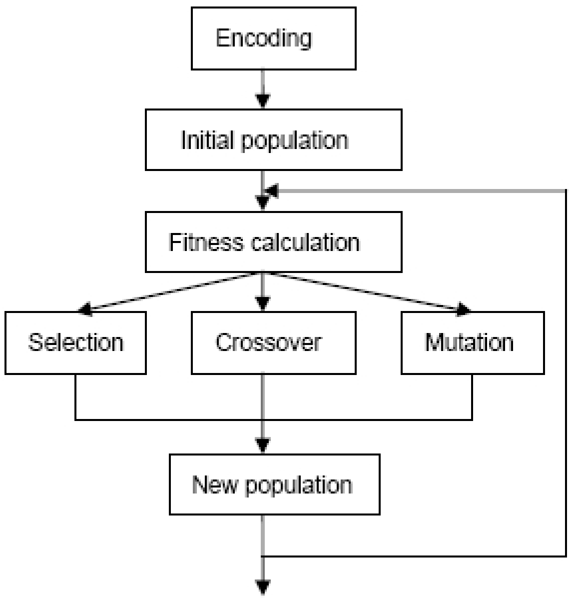


Fig 4: The flow chart of GA

4. Proposed Model

The model is proposed for image denoising based on genetic algorithm and Dual-Tree complex wavelet transform (GA- 2-D DT-CWT). In the model, based on genetic algorithm, the parameters are selected for DT-CWT in image denoising such as decomposition levels, threshold value and threshold, hard or soft threshold. Where, each chromosome is used to encode the decomposition levels, threshold value and threshold algorithm, hard or soft threshold. The proposed model is simple to implement and computationally more efficient. The main procedure of the model is described as follow steps:

Step1. Using binary encoding scheme for each weight encoded and randomly generates initial population in genetic algorithm.

Step2. The fitness (objective) function for genetic algorithm is defined as the Mean Square Error (MSE), MSE is defined as [14]:

$$MSE = \frac{1}{N}\sum_{r}^{N-1}\sum_{c=0}^{N-1}\left[\hat{I}(r,c) - I(r,c)\right]^2 \quad (3)$$

Where I(r,c) represent original SAR image, Î(r,c) represent denoising SAR image and N represent the number of pixels in the SAR image, calculate the error function to determine its fitness. If the error function calculated is greater than margin of error, it's less fitness.

Step3. The individual who have a high fitness would be to the next generation by genetic.

Step4. Crossover and mutation operation can be used to deal with the current population to produce the next generation of the population. Line crossover is defined as

$$\begin{cases} c_1 = p_1 a + p_2(1-a), \\ c_2 = p_1(1-a) + p_2 a, \end{cases} \quad (4)$$

where a is a random number distributed uniformly in [0,1]. P_i and c_i (i=1, 2) denote parents and offspring chromosome respectively. The operation of mutation can be expressed as follows

$$if\ \chi \ \le \ p_m \Rightarrow$$

$$v' = \begin{cases} v + (v_{\max} - v)\left(\sigma\left(1 - \dfrac{gen_c}{gen_{\max}}\right)^b\right), & \gamma > 0.5, \\ v - (v - v_{\min})\left(\sigma\left(1 - \dfrac{gen_c}{gen_{\max}}\right)^b\right), & \gamma \le 0.5, \end{cases} \quad (5)$$

where χ, σ, γ are uniform random variables in [0,1]. P_m is the mutation rate. v is the variable to be mutated, its randomly determined uniformly and definition domain is [$v_{\min}$, $v_{\max}$]. v' is the variable after mutation. gen_c is the number of current generation. $gen_{\max}$ is the maximum number of generations. b is the parameter for mutation.

Step5.Then decoding the new population and calculate the error.

Step6. Repeat step2 to step5 Go to step 3 until obtaining determined fitness value

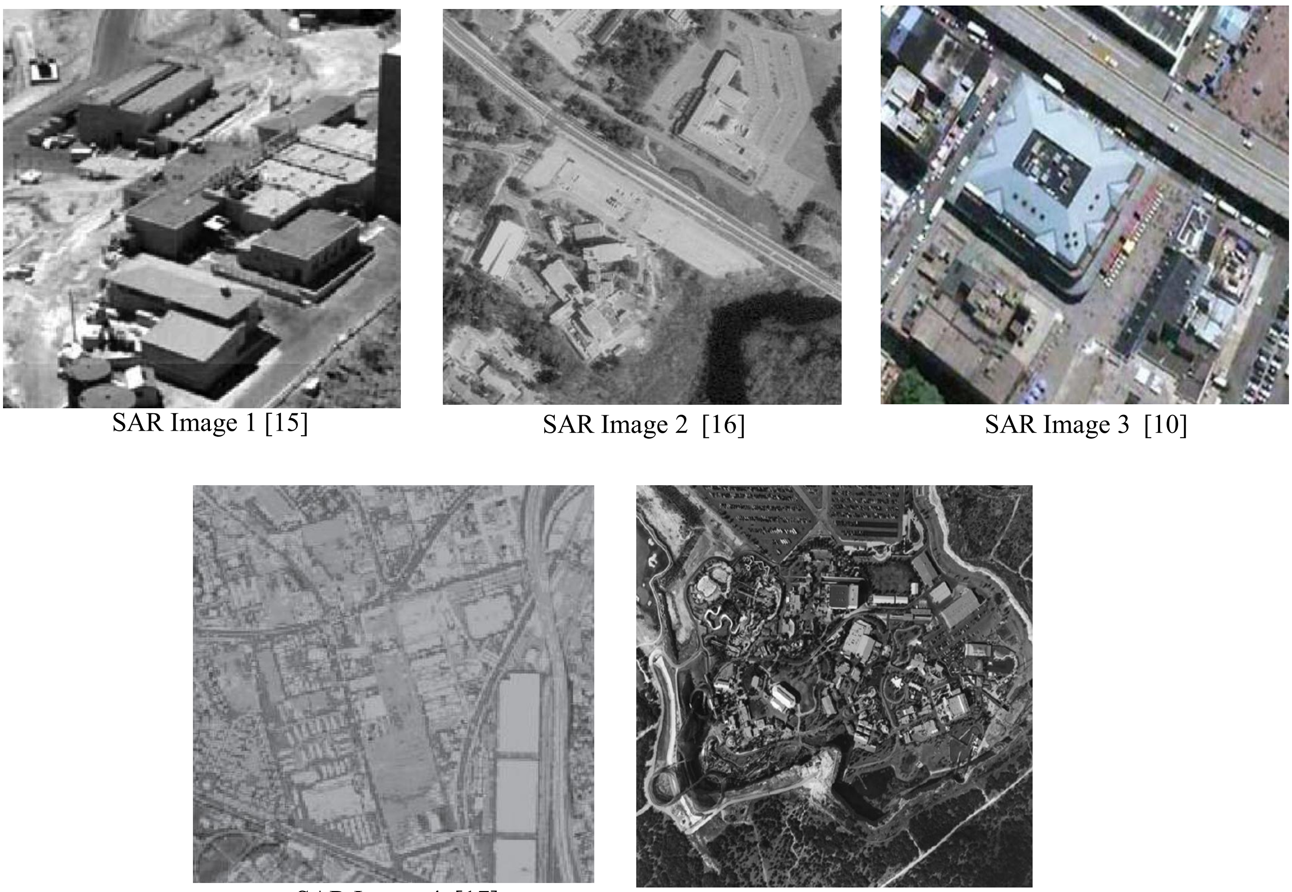
Step 7.Construct the Dual-Tree Complex wavelet denoising with the selected string.

- Perform Dual-Tree Complex wavelet transform for SAR image at level which obtained by GA
- Threshold wavelet coefficients at threshold value with hard or sot threshold whose obtained by GA
- Perform inverse transform for these coefficients to reconstruct the denoised image

5. Simulation and Results

In this section, five SAR images are used as test SAR images [10,15,16,17] with Speckle noise in proposed model . Fig. 5 shows the SAR images used to test proposed algorithm. The proposed algorithm is build by MATLAB 7.In proposed model, Parameter settings for the genetic algorithm are mutation rate=0.05, crossover rate=0.65, population size=20 and binary coding to the chromosomes. To assess the performance of proposed model, it is compared with other methods for SAR image denoising based on genetic algorithm such as Dual-Tree wavelet transform (GA-2-D DT-WT) and wavelet transform(GA-2-D-WT) and also compared with same methods without using genetic algorithm such as (2-D DT-CWT), (2-D DT-WT) and (2-D-WT). The measure criterion for comparison was PSNR, which can be calculated directly from the original and reconstructed data. The relation of peak signal to noise ratio (PSNR), defined it as shown in equating (6) below [14]:

$$SNR_{PEAK} = 10 \log \left(\frac{(255)^2}{\frac{1}{N} \sum_{r=0}^{N-1} \sum_{c=0}^{N-1} \left[\hat{I}(r,c) - I(r,c) \right]^2} \right) \quad (6)$$



SAR Image 1 [15] SAR Image 2 [16] SAR Image 3 [10]

SAR Image 4 [17] SAR Image 5 [15]

Fig. 5: Five simulated SAR images used in the paper.

Where I(r,c) represent original SAR image, Î(r,c) represent denoising SAR image and N represent the number of pixels in the SAR image. The performance of the proposed method that has been proposed in this paper is investigated with simulations. Speckle noise is added to a different SAR images. Some important observations can be made from the simulation results. The results as shown in table 1. Analysis of simulated images led us to conclude that: (1) Parameters (decomposition levels and threshold, threshold, hard or soft threshold) of 2-D DT-CWT, 2-D DT-WT and 2-D-WT can be optimized and selected automatically with GA, and aimless selecting of parameters may be avoided. (2) From the improvement of PSNR, we can see that the denoising performances of GA- 2-D DT-CWT, GA-2-D DT-WT and GA-2-D WT are better than those of the general denoising methods based on 2-D DT-CWT, 2-D-DT-WT and 2-D WT. The best generation of the GA method is obtained in the aspect of optimizing fitness function.

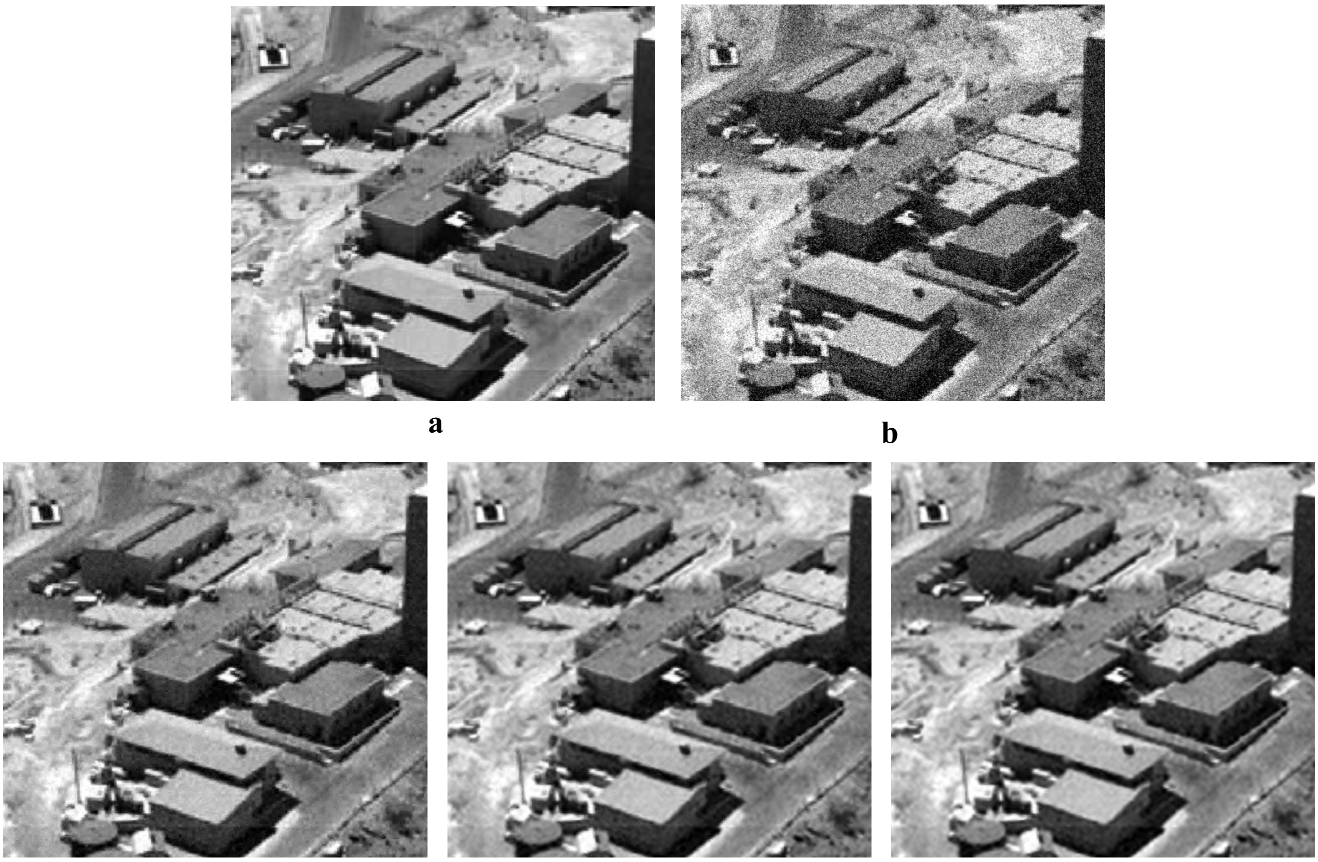
Table 1 Image denoising measure obtained by several denoising Methods and proposed model for different SAR images.

		SAR Image 1	SAR Image 2	SAR Image 3	SAR Image 4	SAR Image
Noisy Image	PSNR	58.0375	58.0800	58.0529	58.0761	58.0729
2-D-WT	PSNR	57.6455	60.3472	60.1955	63.4859	63.8437
2-D-DT-WT	PSNR	60.7164	63.9442	64.2229	65.1262	65.5488
2-D-DT-CWT	PSNR	62.6760	65.4771	66.3464	67.5847	66.4029
GA-2-WT	PSNR Decomposition Levels Hard or Soft Threshold Threshold	64.5328 2 Soft Threshold 35.4	65.0911 2 Soft Threshold 34.1	63.7765 2 Soft Threshold 30.3	66.6166 2 Soft Threshold 40	64.3235 1 Soft Threshold 20.2
GA-2-D-DT-WT	PSNR Decomposition Levels Hard or Soft Threshold Threshold	66.5284 2 Soft Threshold 25.1	66.6137 3 Soft Threshold 19.1	66.5139 2 Soft Threshold 24.7	68.4764 2 Soft Threshold 30.2	66.8812 1 Soft Threshol 24.9
GA-2-D-DT-CWT (proposed model)	PSNR Decomposition Levels Hard or Soft Threshold Threshold	67.1910 2 Soft Threshold 19.8	67.5670 3 Soft Threshold 20.2	67.2144 2 Soft Threshold 19.5	68.9711 2 Soft Threshold 20.6	67.4876 1 Soft Threshol 20.1

(3) Denoising performances of GA- 2-D DT-CWT are better than those of GA- 2-D DT-WT and GA- 2-D WT whether in the improvement of PSNR or in visual quality. Fig. 6 shows the noise free image, the image with noise added, the denoised image with GA-2-D WT, the denoised image with GA-2-D DT-WT, and the denoised image with GA- 2-D DT-CWT. Prove that, the proposed model for image denoising technique performs better results than those of the general denoising .

6. Conclusion

In this paper, we have introduced a new model to SAR image denoising by combine Dual-Tree Complex Wavelet denoising with genetic algorithm. In the proposed model, using genetic algorithm to guide the selection of parameters (decomposition levels, threshold value and hard or soft thresholding) in wavelet deniosing. The effectiveness of the method was validated by the analysis of simulated. The method proposed in this paper is also applicable to other denoising methods based on wavelet transform, such as GA-2-D DT-WT and GA-2-D WT. Simulation results show there is much difference between method proposed and other method for SAR images denoising and it shows that performance of proposed method yields significantly improved visual quality as well as better PSNR compared to the other techniques in the denoising SAR image, there for the speckle noise can be reduced effectively by using proposed method



a b

c d e

Fig. 6 Results of various speckle suppressing methods. (a) Original image. (b) Simulated speckle SAR image .(c) Image denoised using GA-2-WT . (d) Image denoising using GA-2-D-DT-WT. (e) Image denoising using GA-2-D-DT-CWT

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