A Review of SAR Hybrid De-Speckling Methods

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Abstract. Significance of high resolution SAR imagery is irrefutable in Earth monitoring applications as it provides valuable information to be analyzed. To examine this information, post image processing techniques such as speckle noise removal, segmentation, edge and object detection are necessary to per-form. Despeckling among them is the fundamental process that makes images visually appealing and comprehensible. This survey paper thus focuses on this primary process and investigates about the recent two-step hybrid despeckling techniques that suppress speckle noise in SAR images. The paper briefly talks about the importance of SAR imaging system, the speckle noise that distorts the information contained in them and the despeckling techniques that exist in literature to eliminate the speckle noise. The review, however, studies the hybrid despeckling techniques in detail by discussing advantages and limitations of models these techniques are following. In the end, it will provide suggestions on how to improve these models.

Keywords: SAR imagery · Despeckling · SAR-BM3D · PCA

1 Introduction

For many years, synthetic aperture radar (SAR) imaging systems have been extensively used for monitoring Earth's resources rather than optical imaging systems. SAR imaging systems can capture and provide high resolution images even in the presence of natural obstacles such as absence of light, presence of clouds, dust, snow and drizzle [1, 2]. In contrast, optical imaging systems do not capture clear images in the presence of natural blockages. This all-weather and whole-day acquisition capability of SAR imaging systems makes it more reliable than the early optical imaging systems which get affected by weather conditions and have dependency on daylight [1, 3]. Independence from daylight is achieved by an artificial illumination source installed in the SAR imaging systems. The larger wavelength of microwaves is responsible for all-weather acquisition capability as this wavelength can penetrate through any obstacles present in the atmosphere [1, 3, 4]. Thus, SAR becomes a highly beneficial and reliable source for acquiring Earth's images. Another noticeable characteristic of SAR imaging systems is the high-resolution imagery which is acquired through synthetic aperture. Synthetic

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aperture is obtained by positioning the antenna on moving platforms where antenna continuously sends and receives microwave pulses and computes their aggregate while platform is in motion hovering over the target. High resolution images are achieved through the aggregate computed by SAR imaging system [2, 3].

Figure 1 illustrates the transmitted microwave pulse and its backscattering to comprehend the image formation process of SAR imaging system [3]. All the backscattered microwaves pulses either do not reach the receiving antenna or their phases get interfered with other waves which distorts the information contained in them. This distortion is described as speckle noise which affects the quality of SAR images. Reasons of the speckle noise in SAR images include scattering mechanism and interference of the electromagnetic waves [5]. Researchers categorized the speckle noise as multiplicative noise which follows Rayleigh distribution, however it can also be described as a degradation function which degrades the quality of SAR imagery [6].

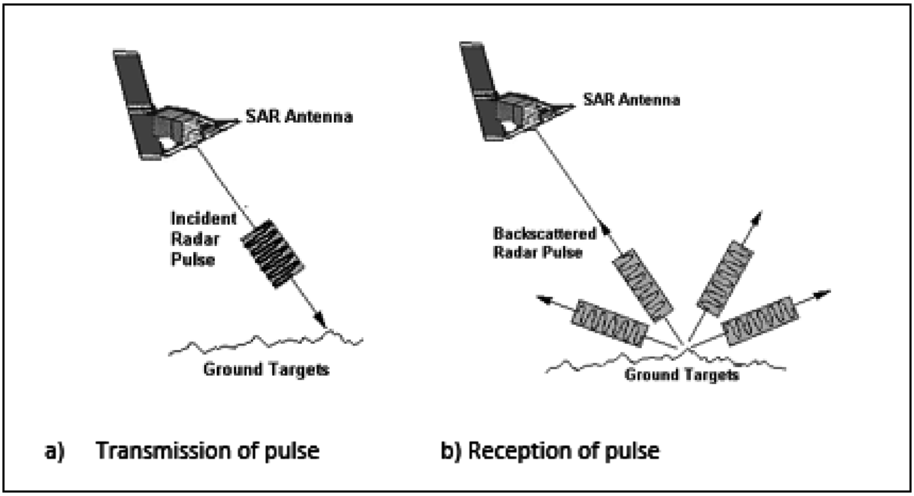

Fig. 1. Transmission and reception of microwave pulses by SAR antenna

Severity of this noise can be observed in Fig. 2 which shows an outdoor noise free and noisy image and clearly demonstrates the effect of noise [7]. Due to the speckle noise, extracting useful information from SAR images becomes difficult which restricts their use in a wide range of applications [1–6]. To restore their useful information such as edges and textures, despeckling becomes necessary as it reduces the amount of speckle and make image contents visible and useful for further processing. Despeckling process is thus necessary to enhance SAR images to be used efficiently and effectively in various applications such as geosciences, forestry, monitoring of climate changes, resource monitoring, oceanology and change detection. To accomplish this task, researchers have devised numerous despeckling techniques in varied domains. As hybrid techniques are the focus of this paper so only these techniques will be discussed in depth in the literature section. However, interested readers are suggested to view the comprehensive surveys on despeckling techniques provided by [5, 8] for better understanding of the despeckling literature. Despeckling filters can be grouped into local [9–11], non-local [12–18], transform based [19–25] and hybrid ones. Local filters despeckle images by alternating the selected pixel's value based on some statistical criterion which is calculated through its neighboring pixels.

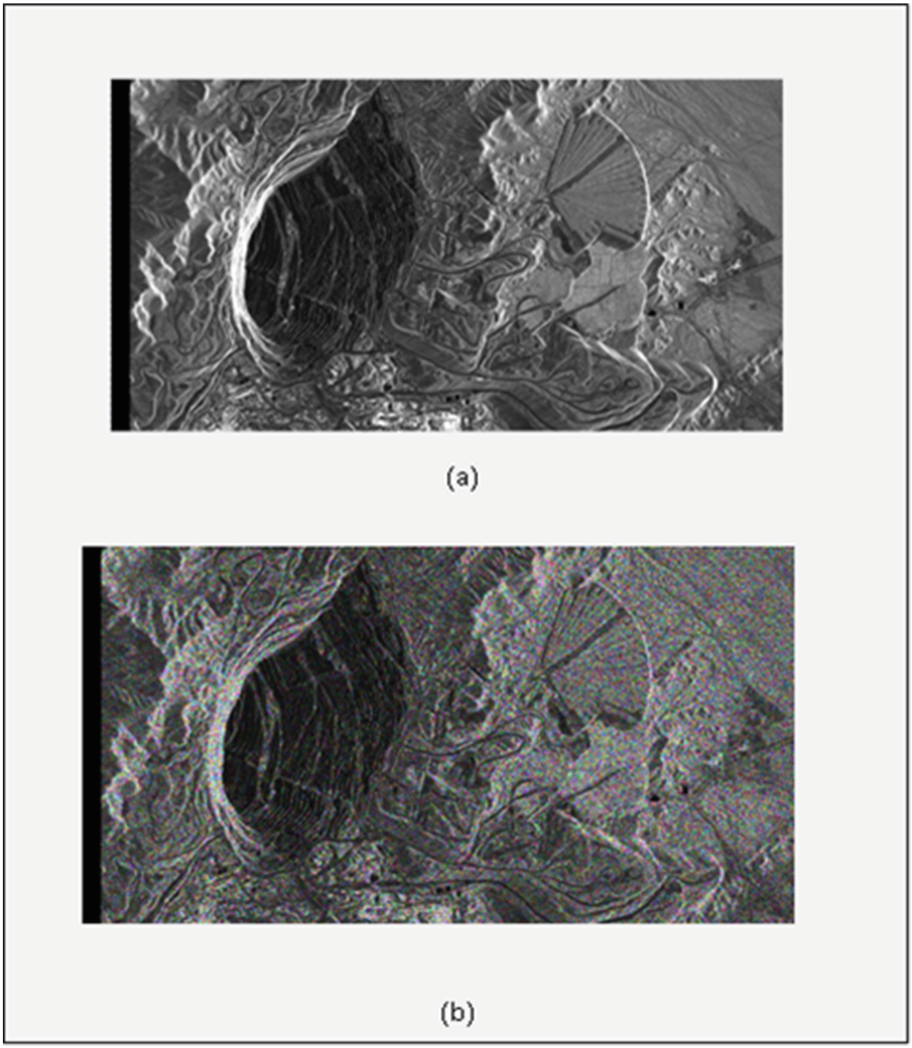

Fig. 2. (a) Noise free satellite image (b) Noisy satellite image

Their concept assumes that neighborhood pixels are of similar statistical nature as that of the selected pixel. This is true in case of homogeneous regions however false for heterogeneous ones. Hence local filters are effective at uniform regions but are responsible for over smoothening fine structures in non-uniform regions [5]. To over-come this problem, researchers have devised non-local filters in past few years. Unlike local filters, these filters look up for a similar pixel or a block anywhere in the image which exhibits the same statistical nature as that of the selected pixel thus increasing the search space. However, these filters perform better at preserving fine structures in heterogeneous regions than local filters [5]. The major limitation of these filters is increased computational cost due to the expanded search space. The transform based approaches are also good at despeckling, but accurate threshold computation and how it should be applied on the image are some serious concerns regarding transforms which put limits to their use [26]. Hybrid approaches in literature combined pixel grouping strategies such as block matching and clustering with various transforms i.e. wavelets and principal component analysis, to despeckle the SAR imagery. These approaches are computationally inefficient but outperform all previous techniques [27, 28]. In this paper existing hybrid approaches will be discussed in Sect. 2. Section 3 provides a discussion on pros and cons of hybrid techniques and their models. And finally, Sect. 4 concludes the paper.

2 Hybrid Filters

The hybrid filter that used pixel grouping strategy and transforms was first proposed by authors to remove additive Gaussian noise [29]. The approach was later modified for removing the speckle noise [27]. This new hybrid filter is dubbed as SAR-BM3D which performed block matching and employed local linear minimum mean square error (LLMMSE) shrinkage transformation instead of hard thresholding as used in the former approach. Although SAR-BM3D performed better than all local, non-local and transform based despeckling techniques, still it is not a cost-effective solution due to its block matching phase. Other problems associated with SAR-BM3D includes introduction of artificial edges into the denoised image and incapability of handling heterogeneity due to usage of lossy transforms i.e. undecimated wavelet and discrete cosine transforms [13, 30]. To overcome the computational complexity of SAR-BM3D, a fast non-local despeckling filter was proposed which replaced the Wiener filter of SAR-BM3D with soft and hard wavelet thresholding for flat and active homogenous blocks respectively [31]. For reducing the complexity of block-matching phase, it used a variable sized search area and a probabilistic early termination criterion. Results revealed that it took less time than SAR-BM3D and showed better despeckling performance than other techniques except SAR-BM3D. The limitations of FANS include over-smoothened edges and inability to preserve textures. Another version of SAR-BM3D known as classification based SAR-BM3D (C-SAR-BM3D) was proposed in [32]. First this filter classified all the pixels as homogeneous or non-homogeneous. Secondly, it filtered the homogeneous regions with simple non-local means filter whereas its strategy remained same for non-homogeneous regions as of SAR-BM3Ds. However, its despeckling results did not out-perform SAR-BM3D due to misclassification of pixels [32].

To improve the despeckling accuracy of SAR-BM3D, another attempt has been made in 2014 [28]. The proposed technique transformed the image into principal component analysis (PCA) domain and get signal PCs for applying k-means clustering.

The clusters were again transformed to PCA domain for applying LMMSE shrinkage. This method showed satisfactory results on homogeneous regions as compared to SAR-BM3D and minimized computational cost. However, it did not perform well on heterogeneous regions. Moreover, k-means clustering produced fixed clusters which is not an optimal solution for grouping of high dimensional data like SAR [33]. An almost similar research was carried out in 2015 [34] which used linear discriminant analysis (LDA) instead of PCA while keeping the remaining strategy same as of [28]. This new research did not provide an optimal solution as well due to k-means clustering [34]. Later, a framework was suggested in [35] which applied SAR-BM3D and homomorphic version of learned simultaneous sparse coding (H-LSSC) on an image to obtain two different estimates. In this method, a soft classifier classified the image content into various classes and computes a despeckled image based on its classification and the two calculated estimates. It did not preserve edges and textures although it performed better despeckling on homogenous regions. In 2015, another attempt has been made to despeckle SAR imagery that utilized the concept of sparse representation [36]. This algorithm does not completely belong to this last category as it did not use any transform. It uses non-local sparse model with iterative regularization technique and demonstrated promising results at some images, however computationally complex when compared with SAR-BM3D. Drawback associated with this technique includes induction of new artifacts in the denoised image.

In 2016, an approach which computed digital elevation model for natural scenes was developed [37]. The designed algorithm performed quite well on homogenous natural scenes as it can describe the scattering mechanism on these regions. But it is incapable of describing the scattering mechanism at man-made structures and non-topographic edges. Sensitivity analysis of SB-SARBM3D has been done afterwards to analyze the influence of scattering model, surface parameters errors, DEM resolution and errors in co-registration step on this filter [38]. Furthermore, the sensitivity analysis of scattering based non-local means despeckling algorithm has been carried out in [39]. Advantages and limitations of proposed hybrid approaches are provided in Table 1.

Table 1. Advantages and limitations of Hybrid approaches

	Technique name	Advantages	Limitations
1.	SAR-BM3D [27]	Preserves image details in both homogeneous and heterogeneous regions and outperforms previous approaches	Computationally inefficient and introduces artifacts in homogeneous regions
2.	FANS [31]	Computationally efficient than SARBM3D	Overall despeckling performance is not superior than SARBM3D due to miss-classification of flat and active regions
3.	C-SARBM3D [32]	No artifacts in homogeneous regions	Manual parameter tuning for each class and poor performance on unstructured texture

(*continued*)

Table 1. (*continued*)

	Technique name	Advantages	Limitations
4.	Clustering Based PCA [28]	Outperforms previous techniques	Could not accurately group pixels as it used k-means for clustering
5.	LDA-Based Solution [34]	Showed satisfactory performance	Clustering accuracy is affected due to k-means
6.	Soft-Classification [35]	Performance is comparable with other approaches	Due to low classification accuracy, results get affected.
7.	SB-SARBM3D [37]	Shows better performance on homogeneous regions than SAR-BM3D	Can only denoise natural scenes as it needs to calculate the digital elevation model

3 Discussion

Hybrid approaches perform better despeckling and are computationally complex than local, non-local and transform based filters. The hybrid techniques can be broadly classified according to the two despeckling models i.e. SAR-BM3D and clustering-based PCA illustrated in Figs. 3 and 4. Techniques that work on the principle of SAR-BM3D used block matching to group similar pixels which is based on the concept of non-local filters. These techniques thus exhibit the limitations of NLM filter such as issue in selecting appropriate similarity measure for comparing blocks and increased computational cost. Increased computational cost makes block matching unsuitable for high dimensional SAR data. FANS, an extension to SAR-BM3D, attempted to reduce the computational cost of SAR-BM3D by introducing the concept of variable search size. This method significantly minimized the computational cost, however, there seems a tradeoff between accuracy and time complexity as FANS do not surpass SAR-BM3D in preserving textures. Some techniques applied classification methods to group the pixels which requires training data set. Absence of data set caused issues of misclassification which leads to poor despeckling performance.

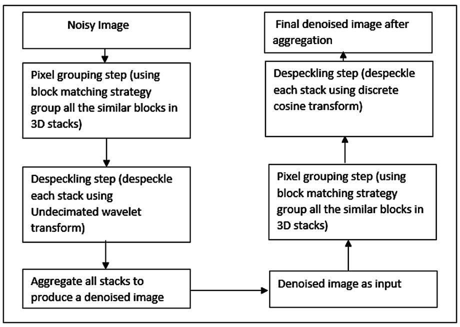

Fig. 3. SAR-BM3D model

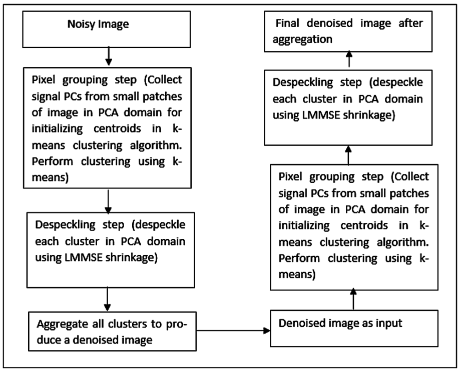

Fig. 4. Clustering-based PCA model

Techniques that follow the second model group similar pixels using k-means clustering. K-means clustering algorithm does not cater high dimensionality and produce fixed number of clusters in both homogeneous and heterogeneous regions. Thus, it may not exactly map the real image contents. However, its lower computational cost makes it time efficient than block matching. Advantages and limitations of pixel grouping strategies are highlighted in Table 2. For removing noise from the groups of similar pixels, both these models used transforms like wavelets and PCA which are inherently lossy and thus affect the preservation of important image contents such as edges and textures.

Table 2. Advantages and limitations of the pre-processing step used in hybrid approaches

Sr. #	Technique name	Advantages	Limitations
1	SAR-BM3D [27]	Achieved better accuracy rates than local, non-local and transform based filters	Computationally inefficient, rare-block problem, hard to find similarity measure, difficult to choose an optimal block size
2	FANS [31]	Computationally efficient than SARBM3D	Still have issues of similarity measure and block size
4	Clustering-Based PCA [28]	Computationally efficient than FANS	Could not accurately group pixels as it used k-means for clustering
3	LDA-Based Solution [34]	Same as Clustering Based PCA	Clustering accuracy is affected due to k-means
5	SB-SARBM3D [37]	Same as SAR-BM3D	Same as SAR-BM3D

Despeckling performance of hybrid techniques depend on how appropriately they group the SAR images into similar regions. For grouping, hybrid techniques used block matching and k-means clustering. These grouping strategies do not provide an optimal solution for segmenting high dimensional SAR data which leaves an open margin for finding an appropriate strategy to improve the despeckling performance. The capability of denoising strategies used by hybrid techniques also affects their despeckling performance. The existing denoising strategies are inherently lossy which arises a need to find the denoising strategy that will better preserve image contents of SAR images.

4 Conclusion

This survey paper provided a brief introduction to SAR imaging systems; how they acquire high resolution images and get corrupted with speckle noise. The review paper has discussed hybrid despeckling techniques in detail. These techniques are categorized in this paper according to the two despeckling models i.e. SAR-BM3D and Clustering-based PCA. These models first group the similar pixels of SAR images via block matching or k-means clustering and afterwards apply transforms i.e. wavelets and PCA to denoise. Limitations of grouping and denoising strategies have also been discussed. From their limitations, it can be concluded that clustering and transforms that remain unexplored in this context should be considered and compared with the existing to find a more appropriate solution towards despeckling of SAR imagery.

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