

# Bayesian despeckling of SAR images based on the Membrane MRF prior model

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**Abstract:** A SAR image can be modeled as the multiplication of the noise-free image and speckles. So the noise-free image can be estimated from the observed image with the Bayesian technique. It's crucial to choose a proper prior model for well matching the SAR images' characteristics. In this article the Membrane MRF model is employed to model the prior information, which overcomes GMRF's problem of sensitivity to parameters. And, pixels in homogeneous and non-homogeneous regions are processed separately by adjusting the model's neighborhood adaptively. Experiments show that not SAR images can be despeckled efficiently while their structures are preserved well.

**Key words:** SAR, speckle, Bayesian, Membrane MRF

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## 1 INTRODUCTION

Speckle noise can be regarded as a strong multiplicative noise affecting all coherent imaging systems including SAR. It hinders data interpretation with standard image analysis tools. Many filters have been developed to reduce it, among which technique based on the Bayesian estimation is one of the most popular (Fabrizio *et al.*, 2006; Alin *et al.*, 2006).

Prior information such as pixels' spatial correlations is introduced via the prior model in Bayesian despeckling. It's crucial to develop a suitable model to successfully remove speckles for Bayesian despeckling. The MRF model becomes popular since S. Geman and D. Geman (1984) applied it to image restoration successfully. Many different MRF models have been developed since then. In a study (Walessa and Datcu, 2000), the Gaussian Markov random field (GMRF) model was used and a visually satisfactory result was achieved. The weighting parameters of GMRF imply information of pixels' spatial correlations within a neighborhood. They must be accurately estimated to avoid mismatching with the image's local characteristics. So GMRF is quite sensitive to parameters. In this paper the Membrane MRF (MMRF) (Bratsolis and Sigelle, 2003) model is used, in which spatial correlations are all determined by the pixels themselves instead of depending on any parameters. Meanwhile, this model is simple and needs low computational loads.

Using MMRF the MAP estimate of the real cross-section

is actually the weighted averaging of the original pixel value and the estimated mean of its neighborhood. If a higher order neighborhood is employed, though homogeneous regions will be effectively despeckled, regions where structures like point targets or edges are present will be blurred, and vice versa. To solve the trade-off between the neighborhood order and the degree of speckle noise removal, an adaptive ordering method is proposed, in which the neighborhood order is automatically adjusted depending on regional characteristics. Experiments show that the Bayesian despeckling using MMRF prior model with neighborhood of adaptive order can effectively suppress speckle noise while preserve fine details.

## 2 THE MRF MODEL AND ITS APPLICATION IN BAYESIAN DESPECKLING

### 2.1 The MRF model

In image processing, the information one isolated pixel can provide is quite limited. A pixel's regional and structural characteristic is embedded in the spatial correlation between itself and its neighborhood which can be described using MRF model mathematically. According to Markov-Gibbs equivalence theory (German S and German D, 1984), the spatial correlation between  $x_r$  and its neighborhood is described using the following function,

$$p(x_r) = \frac{1}{Z_r} e^{-U(x_r, \eta_r)} \quad (1)$$

where  $r$  denotes pixels' serial number,  $Z_r$  a normalizing constant,  $\eta_r$  the set of  $x_r$ 's neighborhood pixels (i. e. in Fig. 1,  $x_r$ 's two order neighborhood includes eight pixels

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surrounding), and  $U(x_r, \eta_r)$  the potential function implicating pixels' spatial correlation.  $U(x_r, \eta_r)$  can be defined accordingly with different image processing tasks, i. e. Generalized Potts model in segmentation, GMRF model in despeckling and texture analysis.

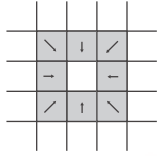


Fig. 1 Two-order neighborhood of MRF model

## 2.2 The framework of Bayesian despeckling based on MRF

The main idea of Bayesian despeckling is to retrieve the "unspeckled" radar backscatter scene  $X$  from the observed image  $Y$  using the Bayesian estimation. When using the MAP approach, that's

$$\hat{X} = \operatorname{argmax}_X p(X|Y) = \operatorname{argmax}_X p(Y|X)p(X) \quad (2)$$

Usually the simulated annealing method is used to achieve the global optimal solution of Function (2). But it converges too slowly because of heavy computing loads. The iterated conditional modes (ICM) (Besag, 1986) approach is often employed in practice to get the suboptimal solution by calculating each pixel's MAP estimation upon iteration. It follows

$$\hat{x}_r = \operatorname{argmax}_{x_r} p(y_r | x_r) p(x_r) \quad (3)$$

where  $p(y_r | x_r)$  is called likelihood function, reflecting the observed pixel value's stochastic characteristic. For intensity image it's usually defined as a Gamma distribution:

$$p(y_r | x_r) = \frac{1}{\Gamma(L)} \left(\frac{L}{x_r}\right)^L y_r^{L-1} e^{-Ly_r/x_r} \quad (4)$$

where  $L$  denotes the number of looks of a SAR image. In Function (3) the term  $p(x_r)$  implies prior information taking into account the neighborhood's influence on despeckling of  $x_r$ .  $\hat{x}_r$  can be calculated given the concrete form of  $U(x_r, \eta_r)$ .

## 3 BAYESIAN DESPECKLING BASED ON MMRF

### 3.1 MMRF model

GMRF is one of the most popular MRF models used in the Bayesian despeckling which is defined as

$$p(x_r) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(x_r - \sum_{j \in \eta_r} \theta_j x_j)^2}{2\sigma^2}\right) \quad (5)$$

where  $\eta_r$  denotes a neighborhood system around  $x_r$ , whose size determines the complexity of the model.  $\theta_j$  and  $\sigma$  are

model parameters describing the spatial correlation between  $x_r$  and its neighborhood and the prediction uncertainty of the model, respectively. For accuracy, order of the neighborhood must be comparatively higher. However, in this case the number of the parameters would increase rapidly, which demands more training data. In the study of Walesa and Datcu (2000), pixels within a rectangle window ( $21 \times 21$  typical) are used for parameter training, but their spatial correlations may not be entirely consistent. Especially when structures like point, line and edge appear, the parameters trained cannot reflect the real spatial correlation between  $x_r$  and its neighborhood. Therefore, GMRF model is quite sensitive to parameters.

In this paper the MMRF is used as the prior model which is given by

$$p(x_r) = \frac{1}{Z_r} e^{-U(x_r)} = \frac{1}{Z_r} \exp\left(-\beta \sum_{j \in \eta_r} (x_r - x_j)^2\right) \quad (6)$$

where the only parameter  $\beta$  is a smoothness factor, determining the contribution of prior information to the MAP estimation. And  $\beta$  has no influence on the spatial correlation between  $x_r$  and  $x_j$  for it is directly embodied in the pixel values' difference. It is obvious that MMRF's description of spatial correlation is free of any parameters but fully subjected to the pixels themselves.

Combined with (3), (4) and (6), it can be inferred that  $\hat{x}_r$  is the positive real solution of the following equation:

$$2\beta N x^2 \left(x - \frac{1}{N} \sum_{x_j \in \eta_r} x_j\right) + L(x - y_r) = 0 \quad (7)$$

where  $N$  is the number of neighborhood pixels. It can be seen that  $\hat{x}_r$  is actually the trade-off between the original pixel value and the neighborhood average. If there's no prior information, the MAP estimate of  $x_r$  will be  $y_r$ . But when MMRF introduced,  $\hat{x}_r$  will tend to the neighborhood average. If pixels within the neighborhood all root from the same backscatter as  $x_r$ , or in other words  $x_r$  and its neighborhood are homogeneous, this will gradually lead to the optimal solution upon iteration. However, if structures appear in the neighborhood, the estimate will be biased. Structures will be blurred but not retained. To put away the disadvantage of fixed neighborhood, an adaptive neighborhood ordering method is proposed.

### 3.2 Adaptive neighborhood ordering

To choose the order adaptively, a problem occurs. That's how to distinguish regions homogeneous or with structures. In Park *et al.*'s research (1999), the regional homogeneity is verified by comparing its coefficient of variation (called CV in the next)  $\sigma/\mu$  with a threshold. There're two disadvantages. Firstly, only boundary pixels of the moving window are used for CV calculating. Though computing loads reduce, more errors come along. Secondly, it is difficult to compute

the threshold analytically upon iteration. In this paper a moving window of fixed size is used to calculate CV with all pixels within it and a statistical method for region distinguishing is proposed rather than thresholding. We regard CV as a random variable whose distribution can be approximately modeled with a two states Gaussian mixture model (GMM). That's

$$p(CV) \triangleq \sum_{i=1}^2 P(i) N_i(\mu_i, \sigma_i^2) \quad (8)$$

in which  $P(1)$  and  $P(2)$  denote weights of the two Gaussian components and their sum equals one.  $N_1$  and  $N_2$  denote the Gaussian distribution with smaller or bigger mean, respectively. The six parameters  $P(1)$ ,  $P(2)$ ,  $\mu_1$ ,  $\mu_2$ ,  $\sigma_1$  and  $\sigma_2$  are estimated using the EM (Carlo, 2007) algorithm which are used in the following statistical

decision. If  $P(1) p_{N_1}(CV_r) > P(2) p_{N_2}(CV_r)$ , the region centred at  $x_r$  is labeled as homogeneous; otherwise, we think structures appear within. The idea is that the region should be distinguished according to which state its CV is closer to.

Fig. 2 (a) is an airdrome SAR image of four looks in which the darker regions are runways, regions of moderate gray levels are lawns, and the brighter are man-made targets such as airplanes, conning towers, *etc.* Fig. 2 (b) gives the result of CV calculation (window size  $7 \times 7$ ). Fig. 2 (c) shows the approximation to the histogram of CV image using GMM model. In Fig. 2(d) region classification is carried out using the stochastic decision method. This finds the basis for adaptive ordering.

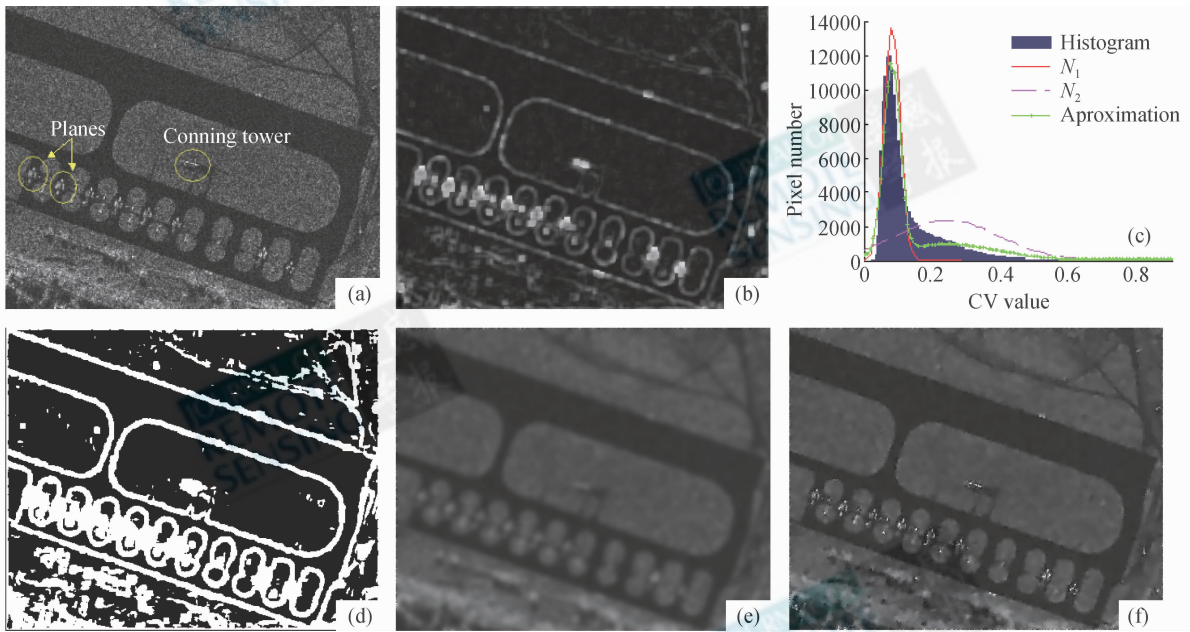


Fig. 2 Despeckling procedure of the proposed method

- (a) SAR image of some airdrome; (b) Image of CV; (c) Approximation to the histogram of CV image using GMM model; (d) Result of region classifying; (e) MMRF despeckling with fixed neighborhood; (f) MMRF despeckling with adaptively adjusting neighborhood

In homogeneous regions, the neighborhood of higher order is chosen and all pixels within are used for calculating the MAP estimation; while in regions with structures, lower order is adopted and only pixels rooting from the same backscatter with the central pixel are selected for calculation. The selection process is similar to the OS algorithm (Rohling, 1983) in the CFAR detection. All pixels within the neighborhood are sorted ascendingly by their absolute distance from the central pixel on intensity values and only the first several are selected out. Though not all the pixels with the same characteristics will be chosen, there's little likelihood to choose the unsuitable ones.

Fig. 2 (f) gives the despeckled image using the proposed adaptively adjusting neighborhood method.

Compared with the fixed neighborhood MMRF despeckling shown in Fig. 2(e), it can be seen the proposed method performs much better in structure preserving.

### 3.3 Flowchart of the proposed method

Fig. 3 shows the flowchart of the proposed Bayesian despeckling method based on the MMRF model with adaptive neighborhood.

## 4 RESULTS

First a simulated SAR image is used for quantitatively analyzing performance of the proposed method in aspects of speckle removal and structure preserving. And a comparison

is done with GMRF and the fix neighborhood MMRF despeckling. Then a real SAR image is used to verify the proposed method.

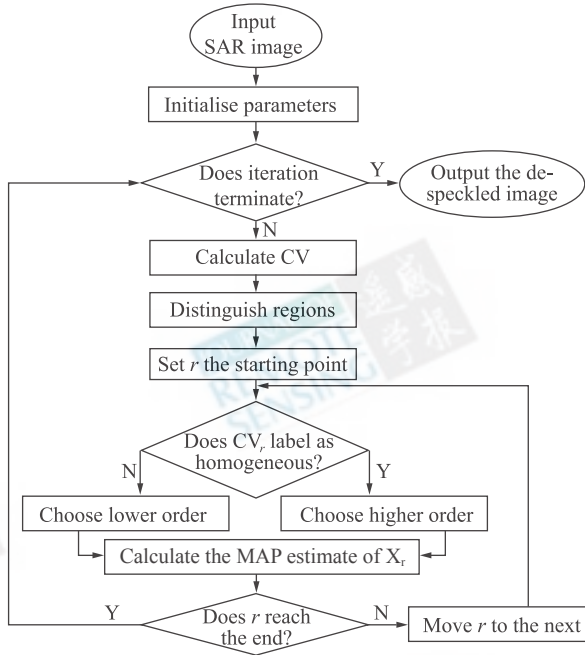


Fig. 3 Flowchart of the proposed method

SNR of the simulated SAR image showed in Fig. 4 (a) is 37dB. It includes some popular structure characteristics like edge, line and point, etc. Two aspects are taken into account for quantitative analysis. They're ENL and edge preserving factor  $\beta$  (Achim *et al.*, 2001) for measurement of despeckling in homogeneous regions (in Fig. 4 (a) region A and B with size  $40 \times 40$  is chosen) and structure preserving respectively.  $\beta$  is defined as follow,

$$\beta = \frac{\Gamma(\Delta S - \overline{\Delta S}, \Delta \hat{S} - \overline{\Delta \hat{S}})}{\sqrt{\Gamma(\Delta S - \overline{\Delta S}, \Delta S - \overline{\Delta S}) \cdot \Gamma(\Delta \hat{S} - \overline{\Delta \hat{S}}, \Delta \hat{S} - \overline{\Delta \hat{S}})}} \quad (9)$$

in which  $S$  and  $\hat{S}$  denote the noise-free and despeckled image respectively.  $\Delta S$  and  $\Delta \hat{S}$  are high-pass filtering results using the standard  $3 \times 3$  Laplacian operator. For ideal edge preserving,  $\beta$  should be close to 1.

From Fig. 4 it can be seen the three mentioned techniques can all suppress speckles in homogeneous regions efficiently. ENL of region A and B is enhanced greatly in Table 1 accordingly. But their performance in edge preserving differs much. MMRF despeckling with adaptively adjusting neighborhood performs much better than the fixed neighborhood MMRF and the GMRF despeckling methods.

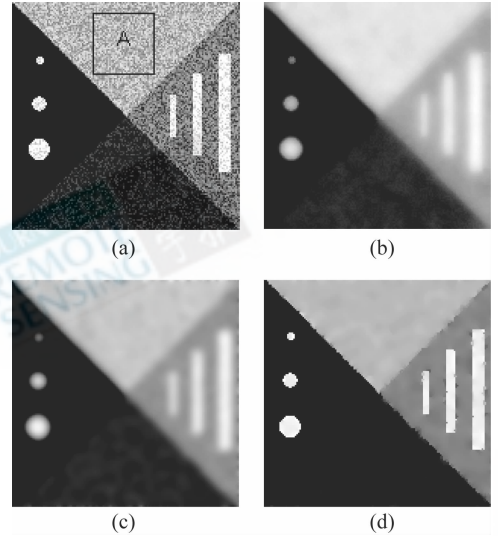


Fig. 4 Despeckling of a simulated SAR image using the three techniques  
(a) Noise added image; (b) GMRF despeckling;  
(c) MMRF despeckling with fixed neighborhood;  
(d) The proposed method

Table 1 Comparison of the three methods

Methods	ENL A	ENL B	$\beta$	Time consuming/m
Noise-free	18.1345	19.3427	0.3338	—
GMRF	500.2245	512.3367	0.2673	10.3
Fixed neighborhood MMRF	460.7689	480.1731	0.2064	1.2
The proposed method	520.3567	540.3525	0.8876	2.6

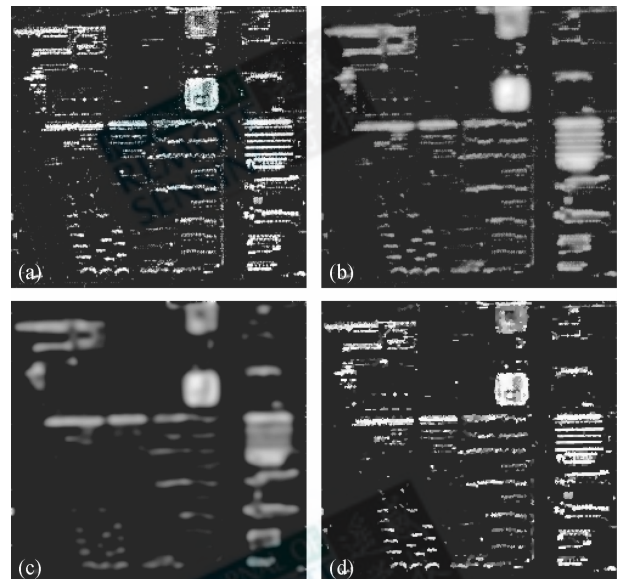


Fig. 5 Despeckling of a real SAR image using the three techniques  
(a) Urban image; (b) GMRF despeckling;  
(c) MMRF despeckling with fixed neighborhood;  
(d) The proposed method

Fig. 5(a) shows a high resolution SAR image of some urban area with eight looks. Man-made buildings look much brighter and have regular shapes. From Fig. 5(b) (c) we can see fixed neighborhood MMRF and GMRF methods blur the image much in despeckling. As a result many man-made buildings are difficult to distinguish. But when the proposed method is used, not only the speckle is efficiently suppressed but also the structure and brightness of man-made buildings are retained (showed in Fig. 5(d)). And the despeckled image is easy for eye interpretation.

## 5 CONCLUSIONS

The Bayesian estimation theory provides a powerful tool for SAR image processing. It's crucial to develop a suitable prior model to extract and utilize all kinds of useful information hidden behind the observed data. In the proposed despeckling method the MMRF model is used to describe pixels' spatial correlation, and its neighborhood is adjusted adaptively according to regional characteristics. Experiments show that not only speckle noises are removed effectively, but also structures are preserved well. And the despeckled image is easier for interpretation with standard image analysis tools.

## REFERENCES

- Achim A, Bezerianos A and Tsakalides P. 2001. Novel bayesian multiscale method for speckle removal in medical ultrasound images. *IEEE Trans. Med. Imag.*, **20**(8): 772—783
- Alin A, Ercan E, Kuruoğlu, Josiane Zerubia. 2006. SAR image filtering based on the heavy-tailed rayleigh model. *IEEE Trans. Image Processing*, **15**(9): 2686—2693
- Besag J. 1986. On the statistical analysis of dirty pictures. *J. R. Statist. Soc. B*, **48**(3): 259—302
- Bratsolis E and Sigelle M. 2003. Fast SAR image restoration, segmentation, and detection of high-reflectance regions. *IEEE Trans. Geoscience and Remote Sensing*. **41**(2): 2890—2899
- Carlo T. Estimating Gaussian Mixture Densities with EM - A Tutorial. <<http://www.cs.duke.edu/courses/spring04/cps196.1/handouts/EM/tomasiEM.pdf>> (Access date: 7 May, 2007)
- Fabrizio A, Tiziano B and Luciano A. 2006. Multiresolution MAP despeckling of SAR images based on locally adaptive generalized gaussian pdf modeling. *IEEE Trans. Image Processing*, **15**(11): 3385—3398
- German S and German D. 1984. Stochastic relaxation, gibbs distribution, and the bayesian restoration of Images. *IEEE Trans. Pattern Analysis and Machine Intelligence*. **6**(6):721—741
- Park J M, Song W J and Pearlman W A. 1999. Speckle filtering of SAR images based on adaptive windowing. *IEE-proc.-Vis. Image Signal Process.* **146**(4): 191—197
- Rohling H. 1983. Radar CFAR thresholding in clutter and multiple target situations. *IEEE Transactions on Aerospace and Electronic Systems*, **19**(4): 608—621
- Walessa M and Datcu M. 2000. Model-Based despeckling and information extraction from SAR images. *IEEE Trans. Geoscience and Remote Sensing*. **38**(5): 2258—2269

# 基于 Membrane MRF 模型的 SAR 图像贝叶斯去斑

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**摘要:** SAR 图像可以看作是真实反映地物后向散射特性的无噪图像与相干斑噪声的乘积,通过贝叶斯估计从图像观测值估计出图像真值即可去除相干斑。而贝叶斯去斑的关键在于建立能与 SAR 图像特性相匹配的先验信息模型。用 Membrane MRF 模型对先验信息建模,克服了以往所用 GMRF 模型对参数估计十分敏感的问题,并通过对该模型邻域结构的自适应调整来分类处理处于匀质区域和含结构特征区域的像元,在有效抑制相干斑的同时较好地保持图像的结构特征。仿真和实际 SAR 图像数据的实验结果,验证了所提方法的有效性。

**关键词:** SAR,相干斑,贝叶斯估计,Membrane MRF