A NEW RATIO IMAGE BASED CNN ALGORITHM FOR SAR DESPECKLING

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ABSTRACT
In SAR domain many application like classification, detection and segmentation are impaired by speckle. Hence, despeckling of SAR images is the key for scene understanding. Usually despeckling filters face the trade-off of speckle suppression and information preservation. In the last years deep learning solutions for speckle reduction have been proposed. One the biggest issue for these methods is how to train a network given the lack of a reference. In this work we proposed a convolutional neural network based solution trained on simulated data. We propose the use of a cost function taking into account both spatial and statistical properties. The aim is two fold: overcome the trade-off between speckle suppression and details suppression; find a suitable cost function for despeckling in unsupervised learning. The algorithm is validated on both real and simulated data, showing interesting performances.

Index Terms— SAR, deep learning, speckle, cnn, denoising

1. INTRODUCTION
Interpretation and understanding of remote sensing images is always an open issue. There are a lot of applications such as object detection, classification, land use segmentation and denoising aiming to extract information by remote sensing data. A very challenging environment is the Synthetic Aperture Radar (SAR) imaging system. SAR images are affected by multiplicative noise, called speckle, that impairs the performance in all applications. In the last decades several despeckling filters have been proposed. Generally, even if there is not a clear-cut classification, the speckle filters are divided in two groups: local and non local filters. The formers produce filtered images where each output pixel is given by averaging values in its neighbourhood, assuming that closer pixels should bring similar information. Filters like Lee, its enhanced version and Kuan filter belong to this class. These filters suffer of edges blurring. On the edge between two structures the pixel values can be very different and averaging the neighbourhood produces smoothness in the filtered image. In order to overcome this issue, non local filters like PPB, SARM3D, FANS and NL-SAR look for similarity in a larger windows search instead of a close neighbourhood. For a review of former method refer to [1], instead for latters to [2] and for FANS to [3]. In the last years, deep learning is spreading in several image processing fields achieving very good results, not less in the remote sensing community. Deep learning methods have been proposed in applications like classification, detection, data fusion and despeckling. In [4] a CNN based approach for SAR target detection is proposed. In [5] and [6] deep learning methods for pansharpening and SAR-optical data fusion are used.

Regarding despeckling, the lack of a clean reference is still an open issue. In order to overcome this problem, [7] train a CNN using simulated data, instead Chierchia et al [8] trains the network on multilook real SAR images.

Following [7], in this work we propose a supervised CNN for despeckling, using a cost function given by a linear combination of a per-pixel and a statistical loss. The aim is to show how extracting statistical information helps the network to solve the usual trade-off between speckle suppression and details preservation. Moreover, the use of a statistical loss can help in future to build a neural network for unsupervised despeckling.

2. CONVOLUTIONAL NEURAL NETWORKS
As said, deep learning and convolutional neural networks are becoming fundamental part of several image processing applications. There is not a predefined structure for a CNN, but in general it is a neural network that, in addition or substitution of fully connected layers use convolutional layers. Generally, different layers are combined: convolutional, pooling, batch-normalization, soft-max, non linealities. The number, the kind and the way in which they are combined depend on the final task.

A generic convolutional layer is define by a set of $M$ kernels of dimension $(K \times K)$. So the $l$-th generic convolutional layer, for $N$-bands input $x^{(l)}$, yields an $M$-band output $z^{(l)}$

$$z^{(l)} = w^{(l)} \ast x^{(l)} + b^{(l)},$$

whose $m$-th component is a combination of 2D convolutions:
\[ z^{(l)}(m, \cdot, \cdot) = \sum_{n=1}^{N} w^{(l)}(m, n, \cdot, \cdot) \ast y^{(l)}(n, \cdot, \cdot) + b^{(l)}(m). \]

The tensor \( w \) is a set of \( M \) convolutional \( (K \times K) \) kernels, while \( b \) is a \( M \)-vector bias.

Let \( \Phi_l \triangleq (w^{(l)}, b^{(l)}) \) be the learnable parameters of \( l \)-th layer. Usually, the output of the layer is followed by an activation function \( g_l(\cdot) \) in order to introduce non-linearities. In this work all the convolutional layers, except the first and the last, are followed by a pointwise ReLU activation function \( g_l(\cdot) \triangleq \max(0, \cdot) \) producing the intermediate layer outputs (the set of \( M \) so-called feature maps)

\[
y^{(l)} \triangleq f_l(x^{(l)}, \Phi_l) = \begin{cases} 
\max(0, w^{(l)} \ast x^{(l)} + b^{(l)}), & l < L \\
w^{(l)} \ast x^{(l)} + b^{(l)}, & l = L
\end{cases}
\]

whose concatenation gives the overall CNN function

\[
f(x, \Phi) = f_L(f_{L-1}(\ldots f_1(x, \Phi_1), \ldots, \Phi_{L-1}), \Phi_L)
\]

where \( \Phi \triangleq (\Phi_1, \ldots, \Phi_L) \) is the whole set of parameters to learn.

In order to train the parameters, several training couples of input and reference output samples must be provided, a cost function and an optimization process must be chosen. The cost function \( L(\cdot, \Phi) \) compares the similarity between predicted and reference outputs. An optimization process tries to minimize \( L \) and depending on it the parameters \( \Phi \) are updated.

3. PROPOSED METHOD

3.1. Speckle Data Simulation

As said before, SAR images are affected by a multiplicative noise called speckle. Let \( Y \) be an intensity SAR image, it can be expressed as [1]:

\[
Y = f(X, N) = X \cdot N
\]

where \( X \) is the noise-free image and \( N \) is the multiplicative speckle. In the hypothesis of fully developed speckle, \( N \) has a Gamma distribution [9]:

\[
p(N) = \frac{1}{\Gamma(L)} N^L e^{-NL}
\]

where \( L \) is the number of looks of the SAR image. An ideal despeckling filter will remove the noise without introducing artefacts and preserving the spatial informations.

In this work simulated data are used following the scheme in equations (1)-(2). We consider three datasets of clean images [7]: scraped Google Maps that provides urban images, UCID and BSD that provide generic images. We simulated speckle with Gamma distribution and apply it on this three datasets.

3.2. Training with Kullback-Leibler divergence

In the proposed method the network (Fig.1) is composed by 10 convolutional layers. In order to speed up the convergence, each layer except the first and last is followed by a Rectified Linear Unit (ReLU). Moreover for the same reason, batch normalization is performed for each layer except the last. The training process is performed by the Stochastic Gradient Descent with momentum, with learning rate \( \eta = 2 \cdot 10^{-6} \) on 30000 \( (65 \times 65) \) training patches and 12000 \( (65 \times 65) \) for the validation.

In this work we focus our attention on a customized cost function which aim is two fold: firstly have better speckle suppression and edge preservation; secondly moving towards unsupervised despeckling.

Given a single band noisy image \( Y \), and the noise-free reference image \( X \), the predicted output is \( \hat{X} = f(x, \Phi) \) (see in Fig.1) and the predicted noise is \( \hat{N} = Y/\hat{X} \)

In this work we propose as cost function \( L \) a linear combination given by

\[
L(x, \Phi) = ||f(x, \Phi) - X||^2 + \lambda \sum_i \log \frac{p_N(i)}{p_N(i)} \cdot p_N(i) \tag{3}
\]

where the first term is the Mean Square Error (MSE) between output and its reference, while the second one is the Kullback-Leibler divergence (KL) between the predicted noise probabilities distribution \( p_{\hat{N}} \) and that of simulated speckle noise \( p_N \) (that follow the Gamma distribution).

With this cost function the network predicts the clean image taking into account the statistical speckle properties. MSE forces the network to predict directly the image by a per pixel comparison with the reference, and KL ensures that the removed noise has probability distributions as close as possible to the Gamma distribution.

As said in previous sections, all the methods show a trade-off between speckle reduction and edge preservation. With
the combination in equation (3) we try to preserve both spatial and spectral informations. Moreover, using a cost function like $L_2$ means to use a cost function that is independent from the reference and it can be an eligible cost function for despeckling in unsupervised neural networks. Based on the adopted methodologies, the proposed technique will be referred as Kullback-Leibler Despeckling Neural Network (KL-DNN) algorithm.

![Reference Noisy PPB FANS KL-DNN]

**Fig. 2:** Results on simulated images: clip1 (above), clip2 (bottom)

### 4. EXPERIMENTS

The proposed method is tested on both simulated and real SAR images and a comparison two of the most accredited despeckling algorithms, PPB [10] and FANS [3], is conducted. Fig. 2 shows the results on two simulated clips. KL-DNN seems to have better performance compared with PPB and FANS. PPB tends to be oversmoothed on both clips loosing a lot of spatial details. FANS preserves the details better respect PPB but suffers of oversmoothing mainly on small objects. For example, in the first clip FANS misses all the cars in the parking lot, instead in the second clip the edge of the buildings are blurred. Moreover some distortions appear on the roof. Regarding KL-DNN, on clip1 it better preserves small objects like cars. Moreover the image seems more detailed than PPB and FANS. In clip2 KL-DNN has similar performances to FANS, even if the edge of building and spatial details like foliages of trees are better preserved. The disadvantage of KL-DNN is that it suffers of distortion on smooth surfaces: in the parking lot and on the building’s roof some dark spots appear.

In order to have a numerical assessment, for the simulated data in which the clean reference is available, the SSIM, PSNR and SNR indexes are computed. Tab. 1 confirms the previous consideration: KL-DNN shows an improvement with respect to PPB and FANS mainly on the first clip; regarding the second clip the gain respect FANS is more slight.

![SSIM PSNR SNR]

(a)

![SSIM PSNR SNR]

(b)

![M-index KL div]

(c)

**Table 1:** Numerical Results: a) evaluation on simulated clip1. b) evaluation on simulated clip2. c) evaluation on real SAR image

### 5. CONCLUSIONS

In this work a convolutional neural network for despeckling is proposed. We use a cost function that relies on per-pixel distance between output and reference and, at the same time, on the statistical properties of the noise. The use of this cost function helps the network to suppress the noise while preserving spatial details. Despite some spatial distortions, the
proposed method seems to have better detail preservation than other methods, mainly on small objects. In fact, more small details are preserved which is a key feature for the scene interpretation of the remote sensing image.

6. REFERENCES

[1] F. Argenti, A. Lapini, T. Bianchi, and L. Alparone, “A tutorial on speckle reduction in synthetic aperture radar images,” IEEE Geoscience and Remote Sensing Magazine, vol. 1, no. 3, pp. 6–35, Sept 2013.

[2] C. A. Deledalle, L. Denis, G. Poggi, F. Tupin, and L. Verdoliva, “Exploiting patch similarity for sar image processing: The nonlocal paradigm,” IEEE Signal Processing Magazine, vol. 31, no. 4, pp. 69–78, July 2014.

[3] D. Cozzolino, S. Parrilli, G. Scarpa, G. Poggi, and L. Verdoliva, “Fast adaptive nonlocal sar despeckling,” IEEE Geoscience and Remote Sensing Letters, vol. 11, no. 2, pp. 524–528, Feb 2014.

[4] S. Chen and H. Wang, “Sar target recognition based on deep learning,” in 2014 International Conference on Data Science and Advanced Analytics (DSAA), Oct 2014, pp. 541–547.

[5] G. Scarpa, S. Vitale, and D. Cozzolino, “Target-adaptive cnn-based pansharpening,” IEEE Transactions on Geoscience and Remote Sensing, vol. 56, no. 9, pp. 5443–5457, Sep 2018.

[6] Giuseppe Scarpa, Massimiliano Gargiulo, Antonio Mazza, and Raffaele Gaetano, “A cnn-based fusion method for feature extraction from sentinel data,” Remote Sensing, vol. 10, no. 2, 2018.

[7] P. Wang, H. Zhang, and V. M. Patel, “Sar image despeckling using a convolutional neural network,” IEEE Signal Processing Letters, vol. 24, no. 12, pp. 1763–1767, Dec 2017.

[8] G. Chierchia, D. Cozzolino, G. Poggi, and L. Verdoliva, “Sar image despeckling through convolutional neural networks,” in 2017 IEEE International Geoscience and Remote Sensing Symposium (IGARSS), July 2017, pp. 5438–5441.

[9] R. Touzi, “A review of speckle filtering in the context of estimation theory,” IEEE Transactions on Geoscience and Remote Sensing, vol. 40, no. 11, pp. 2392–2404, Nov 2002.

[10] C. A. Deledalle, L. Denis, and F. Tupin, “Iterative weighted maximum likelihood denoising with probabilistic patch-based weights,” IEEE Transactions on Image Processing, vol. 18, no. 12, pp. 2661–2672, Dec 2009.

[11] Luis Gomez, Raydonal Ospina, and Alejandro C. Frery, “Unassisted quantitative evaluation of despeckling filters,” Remote Sensing, vol. 9, no. 4, 2017.