A COMPARATIVE STUDY OF SPECKLE REDUCTION IN SAR IMAGERY: CONVOLUTIONAL AUTOENCODER VERSUS ADAPTIVE FILTERS

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KEY WORDS: speckle, SAR imagery, deep learning, autoencoder, image processing

ABSTRACT:

The speckle effect can significantly hamper the quality of Synthetic Aperture Rada (SAR) imagery, making interpretation challenging. Different methods have been developed for speckle suppression, but their limitation call for more innovative solutions. Deep learning-based approaches, in particular Convolutional Neural Networks (CNNs) have emerged as promising alternative. However, CNNs seldom require clean images (speckle-free) as ground truth for training, a relevant challenge in the SAR imagery context. This study propose a self-supervised learning approach, implementing the autoencoder architecture in a model named SpeckleReducer, aiming to reduce speckle without using ground truth. A subset of the SEN12MS dataset was used for this purpose. The performance of SpeckleReducer was compared to two traditional adaptive filters using the Speckle Suppression Index (SSI). Although SpeckleReducer performed less effectively than expected, its self-supervised nature represents a significant advantage, given the problem of finding ground truth data. This study provides understanding of the potential and limitations of the proposed model and suggests directions for future improvements.

1. INTRODUCTION

Synthetic Aperture Radar (SAR) is a powerful remote sensing technology with a number of applications, ranging from land cover mapping, environmental and agricultural monitoring, and disaster management (Curlander and McDonough, 1991). Thanks to microwave radiation sent to the Earth's surface, SAR technology allows to acquire high-resolution imagery regardless the weather and the light conditions (Oliver and Quegan, 1998). Thanks to this remarkable property, SAR distinguishes from optical remote sensing for its suitability to be applied in areas seldom covered by clouds, such as the tropics.

However, SAR imagery is frequently affected by a granular effect, known as speckle, that significantly degrades the quality of the acquired data and make the interpretation challenging (Goodman, 1976). Due to speckle, SAR imagery can show grey level variations that may occur between adjacent resolution cells. These variations create a heterogeneous texture, caused by the coherent radiation used by radar systems (Qiu et al., 2004). This effect is also known as "salt and pepper" because of the significant changes of brightness between neighbouring pixels. The origin of speckle is due to the fact that radar systems use a single wavelength radiation, and its distribution seems to be random.

Formally speaking, speckle does not represent a noise but a signal, since it is caused by a repetitive physical phenomenon. However, since it is very difficult to extract useful information from speckle in a single radar image, it is often considered and treated as a noise. Speckle reduction has become an essential pre-processing step for SAR image analysis, and several speckle suppression techniques have been developed.

Common techniques include digital image filtering using moving windows (kernels), including adaptive filters such as Lee filter (Lee, 1980), Frost filter (Frost et al., 1982) and Kuan filter (Kuan et al., 1985 and 1987). These methods are based on local statistics and were designed to preserve the most relevant features in an image, such as edges and textures, wile reducing the speckle effect. Although this filters have largely been used in the past with good results, they have also shown some limitations: for instance, the assumption of a homogeneous noise model and the risk of over-smoothing the image (Argenti and Alparone, 2002).

Advances in deep learning applications for image processing ver the last two decades present a valuable alternative for speckle suppression in SAR imagery. Convolutional Neural Networks (CNNs) have shown impressive results in a range of image processing tasks, including denoising (Zhang et al., 2017). A number of studies has been carried out during recent years specifically regarding the usage of deep learning for SAR imagery despeckling (Mullissa et al., 2020; Yang et al., 2019; Lattari et al., 2019; Zhang et al., 2018; Zhang and Sun, 2020). However, most of these methods often require a large amount of speckle-free images as ground truth for training, which are challenging to obtain in the context of SAR imagery.

In this work, a self-supervised learning approach based on the autoencoder architecture is proposed (Larrue et al., 2018). The focus is on comparing the performance of the proposed model, named SpeckleReducer, against traiditional adaptive filters. The aim is to evaluate the effectiveness of this network without the use of ground truth during training, and to compare this model's performance to the aforementioned deterministic techniques. This comparison was carried out using speckle reduction metrics.

2. MATERIALS AND METHODS

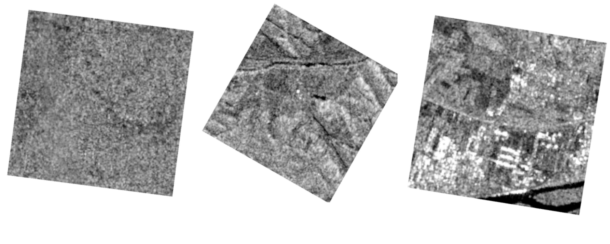

Figure 1: Examples of Sentinel-1 images contained in the SEN12MS dataset

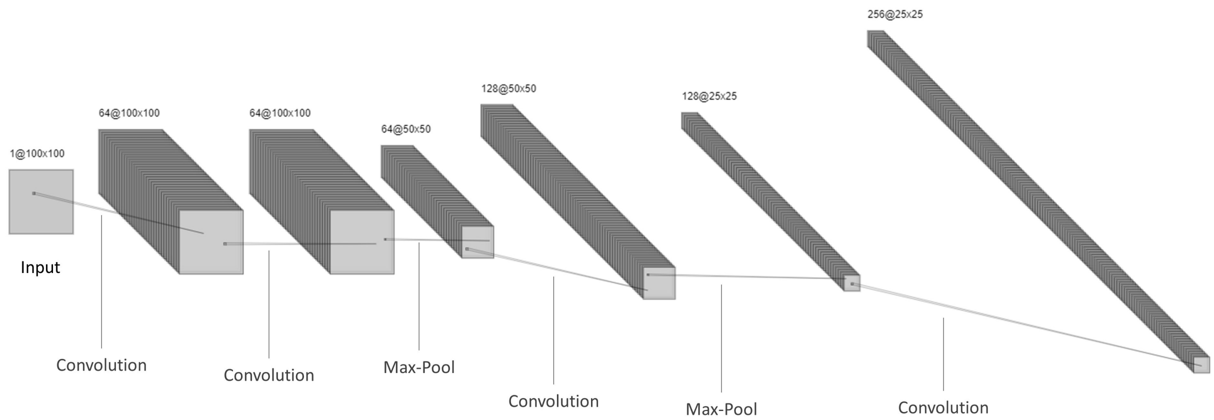

Figure 2: Encoder architecture of SpeckleReducer

2.1 Dataset

A subset of the SEN12MS dataset (Schmitt et al., 2019) was used for this study. This dataset, made of freely available satellite and satellite-derived data, comprises of 180,662 triplets of Sentinel-1 dual-polarimetric SAR data, Sentinel-2 multi-spectral images and land cover maps based on MODIS data. This dataset comprises multiple geographical regions with a variety of land cover types. This variability is useful to make the model learn to remove speckle from different land covers, avoiding biases towards a specific type of scene. For this work, a subset of the SEN12MS dataset was used, focusing on the Sentinel-1 imagery. For the preparation of this dataset, the authors made use of ground-range-detected (GRD) products acquired with interferometric wide swath (IW) mode. SEN12MS contains both VV and VH polarized images, exploiting all the potential of Sentinel-1. The authors carried out ortho-rectification of the images but leaving any further pre-processing step, included speckle filtering, to the end users.

Figure 1 shows a few examples of Sentinel-1 images contained in the SEN12MS dataset. In total, 9497 images were used. The original image size was 256x256, but for computational reasons they were center-cropped to 200x200 images during training. The dataset was divided in three parts: training, validation and testing, respectively with a proportion of 0.60, 0.20 and 0.20. In order to further increase the variability of the dataset, data augmentation was applied. In particular, random horizontal and vertical flip were applied. The augmentations were executed on-the-fly when loading the batches during training, without inflating the original dataset.

2.2 The network

Autoencoders are neural networks that, thanks to their bottleneck structure, learn a compressed representation of the input data (Bajaj et al., 2020). Autoencoders are made of two main parts: the encoder, which learns to compress the input image into a lower-dimensional feature representation, and the decoder, which goals is to reconstruct the input image from the compressed representation. The compression step is what forces the network to learn the most important spatial features of an image, thus trying to remove less important information (such as speckle, in this case). SpeckleReducer is made of an encoder and decoder connected to each other through a middle portion which contains 2 redisual connection blocks. The internal structure of each residual block has the goal to learn an identity function, and the input is added to the output of each block. The usefulness of redisual blocks is to preserve relevant features of the input images. The encoder is made of a sequence of convolution and max-pooling operation. The architecture of the encoder of SpeckleReducer is shown in Figure 2. The decoder mirrors the architecture of the encoder, using up-sampling to return the image with the same size as the input. Figure 3 show the structure of the decoder of SpeckleReducer. Rectified Linear Unit (ReLU) is used as activation function (Fukushima, 1975) after each convolutional layer.

2.3 Training

The model was trained for 20 epochs, using a learning rate of 0.001. The Mean Squared Error (MSE) was used as loss function. This choise was motivated by the nature of the denoising task, which can be seen as a regression problem where the goal is to predict clean pixel values. The MSE loss function effectively measure the average squared differences between our model's predictions and the true values, providing a suitable feedback for the training process. In order to prevent overfitting, data regularization techniques were involved. In particular, weight decay and batch normalization (Ioffe and Szegedy, 2015) were applied. Adam (adaptive moment estimation) optimization algorithm (Kingma and Ba, 2014) was applied in SpeckleReducer. The model was trained and tested using the Google Colab environment, exploiting the hardware resources provided by Google.

2.4 Speckle suppression performance

Speckle Suppresion Index was used to compare the performance in suppressing speckle between SpeckleReducer and two adaptive filters, Frost and Lee filters Frost et al., 1982; Lee, 1980). Both these adaptive filters were used with a window size of 5x5. The SSI calculates the coefficient of variance of the filtered images, normalizing it by that of the noisy (unfiltered) image. It is defined as:

$$SSI = \frac{\sigma_{I_f}}{\mu_{I_f}} * \frac{\mu_I}{\sigma_I} \tag{1}$$

where I_f = filtered image
I = noisy image

The filtered image is expected to have a lower variance than the original image. SSI values are normally below 1.0, and the lower this value is, the more impactful the speckle suppression was (Sheng and Xia, 1996). In this case, since a time series was not available, no homogenous areas were identified and the SSI was calculated over the whole images.

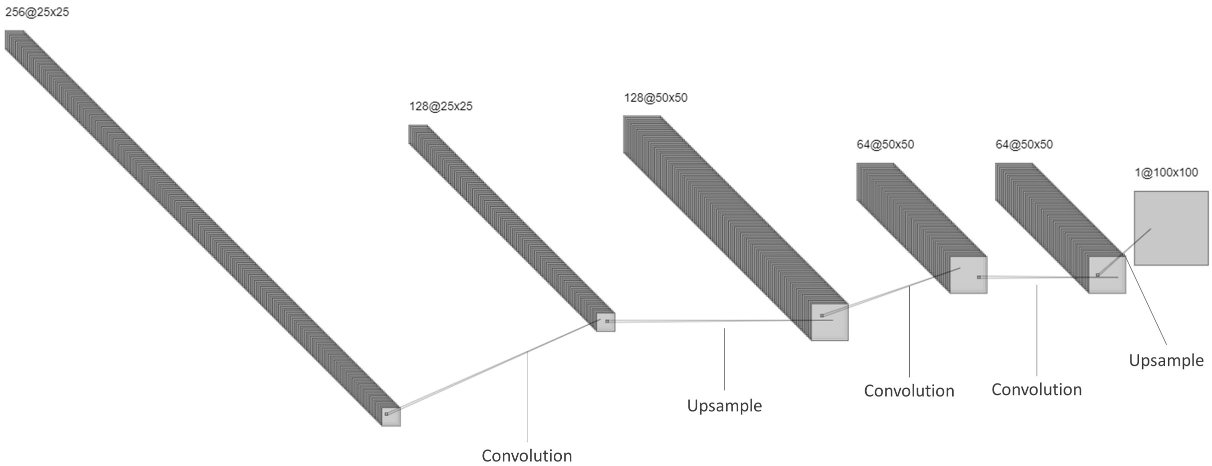

Figure 3: Decoder architecture of SpeckleReducer

3. RESULTS

Three images of the test set were used to show the performance of SpeckleReducer in comparison with Frost and Lee filters. Visual results are shown in Figure 4, while. Table 1 reports the SSI values obtained with the different methods. For the first image, SpeckleReducer achieved an SSI of 0.71, which is higher than Frost Filter (0.68) but lower than the result obtained with Lee filter (0.76). This trend seems to be similar for the second and third images, where SpeckleReducer consistently achieves a lower SSI than Lee and Frost filter.

Image	SSI		
	SpeckleReducer	Lee	Frost
1	0.71	0.76	0.68
2	0.91	1.1	0.97
3	0.97	1.09	1.04

Table 1: SSI values obtained with the applied filters

4. DISCUSSION

The performance of SpeckleReducer was found to be less effective than expected. While the model was successful in reconstructing the images, its speckle reduction performance was mediocre. Even so, also the adaptive filters performed poorly, as evidenced by the SSI values obtained with the different methods. The results suggest that the performance of the applied methods varied depending on the image used.

These results can be interpreted in different ways: on one hand, it could be that SpeckleReducer worked in a more conservative way when trying to denoise, maintaining more of the original features in the input image at the cost of leaving more speckle. On the other hand, it could be that the used adaptive filters worked more aggressively in their despeckling, removing more speckle but also potentially removing some of the original image features. However, more detailed analysis are required to determine the exact reasons for these performance differences.

One potential reason for this poor performance could be related to the inherent complexity of speckle in SAR imagery (Goodman, 1976). Due to the multiplicative nature of speckle, it presents a unique denoising challenge. The self-supervised nature of SpeckleReducer may lack the ability of discerning between useful image features and noise. On the other hand, adaptive filters are designed for this scope (Frost et al., 1982; Lee et al., 1994) and have been proven to be effective over years of usage (Santoso et al., 2015). In fact, their core concept is the adaptation to the local characteristics of the input image which, accordingly with the selected window size, might be a better approach for dealing with speckle.

However, it is important to remark the potential advantages of deep learning-based approaches.
The possibility of using autoencoder-based architecture for SAR imagery despeckling is an area worthy of continued investigation. The potentiality of such models to be used without any ground truth is particularly valuable, given the challenge of finding clean (denoised) images without speckle in the context of SAR imagery.

Another relevant aspect that could be influencing the performance of SpeckleReducer is the implemented loss function. As stated previously, the MSE loss is used. While it is a common choise for regression problems, it may not be the best suited for the specific inherent properties of SAR speckle. In fact, MSE loss assumes a Gaussian noise distribution, while speckle in SAR follows non-Gaussian, multiplicative models (Chiang et al., 2022). Therefore, future work could explore different loss functions that are better suited to the characteristics of speckle noise, taking into account its statistical properties. The implication of this research would encompass the whole broad field of SAR image processing, informing the development of more effective denoising methods in the future.

5. CONCLUSION

Despite its current limitation, SpeckleReducer represents a promising starting point for further research. In order to improve the network-s performance, future work could involve experimenting with deeper architectures, incorporating more prior knowledge about speckle into the model, or using additional training data (for instance, using the whole SEN12MS dataset, relatively to the Sentinel-1 imagery). Designing a suitable loss function, specific to suppress speckle in SAR imagery, is a crucial aspect that should be addressed in future research. Despite its shortcomings, SpeckleReducer represents a promising starting point for more effective SAR speckle reduction.

5.1 Software availability

The code used for the project is accessible as Google Colab notebook through the URL below:

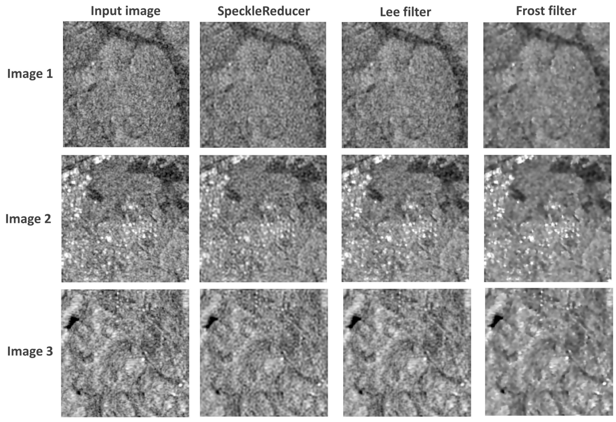

Figure 4: Results obtained with the different filters on 3 images of the test set

https://tinyurl.com/mrxvjfjc
If users want to modify the code, it is necessary to make a copy on their own drive.

REFERENCES

Argenti, F., Alparone, L. (2002). Speckle removal from SAR images in the undecimated wavelet domain. IEEE Transactions on Geoscience and Remote Sensing, 40(11), 2363-2374. doi:10.1109/TGRS.2002.805083

Bajaj, K., Singh, D. and Ansari, M. (2020). Autoencoders Based Deep Learner for Image Denoising. Procedia Computer Science. 171. 1535-1541. 10.1016/j.procs.2020.04.164.

Chiang, C.-Y.. Chen, K.-S., Yang, Y., Zhang, Y., Wu, L. (2022). Radar Imaging Statistics of Non-Gaussian Rough Surface: A Physics-Based Simulation Study. Remote Sens. 2022, 14, 311. https://doi.org/10.3390/rs14020311

Curlander, J. C., McDonough, R. N. (1991). Synthetic Aperture Radar: Systems and Signal Processing. John Wiley Sons. ISBN: 978-0-471-85770-9

Frost, V.S., Stiles, J.A., Shanmugan, K.S., Holtzman, J.C. (1982). A Model for Radar Images and Its Application to Adaptive Digital Filtering of Multiplicative Noise. IEEE Trans. Pattern Anal. Mach. Intell. PAMI-4, 157–166. doi:10.1109/TPAMI.1982.4767223

Fukushima, K. Cognitron: A self-organizing multilayered neural network. Biol. Cybernetics 20, 121–136 (1975). https://doi.org/10.1007/BF00342633

Goodman, J. W. (1976). Some fundamental properties of speckle. Journal of the Optical Society of America, 66(11), 1145-1150. doi:10.1364/JOSA.66.001145

Ioffe, S., Szegedy, C. (2015). Batch normalization: accelerating deep network training by reducing internal covariate shift. arXiv preprint arXiv:1502.03167

Kingma, D. P., Ba, J. (2014). Adam: a method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Kuan, D.T., Sawchuk, A.A., Strand, T.C., Chavel, P. (1985). Adaptive noise smoothing filter for images with signal-dependent noise. IEEE Trans Pattern Anal Mach Intell. Feb;7(2):165-77. doi: 10.1109/tpami.1985.4767641. PMID: 21869255.

Kuan, D.T., Sawchuk, A.A., Strand, T.C., Chavel, P. (1987). Adaptive Restoration of Images with Speckle. IEEE Trans. Acoust. doi:10.1109/TASSP.1987.1165131

Lattari, F., Gonzalez Leon, B., Asaro, F., Rucci, A., Prati, C., Matteucci, M. (2019). Deep Learning for SAR Image Despeckling. Remote Sens. 2019, 11, 1532. doi:10.3390/rs11131532

Larrue, T., Li, Y., Meng, X., Han, C. (2018). Denoising Videos with Convolutional Autoencoders: A Comparison of Autoencoder Architectures. In Proceedings of ACM Conference (Conference'17). ACM, New York, NY, USA.

Lee, J. Sen, 1980. Digital Image Enhancement and Noise Filtering by Use of Local Statistics. IEEE Trans. Pattern Anal. Mach. Intell. PAMI-2, 165–168. doi:10.1109/TPAMI.1980.4766994

Lee, J.S., Jurkevich, L., Dewaele, P., Wambacq, P., Oosterlinck, A. (1994). Speckle filtering of synthetic aperture radar images: A review. Remote Sens. Rev. 8, 313–340. doi:10.1080/02757259409532206

Mullissa, A.G., Marcos, D., Tuia,D., Herold, M., Reiche, J. (2020). deSpeckNet: Generalizing Deep Learning Based SAR Image Despeckling, IEEE Transactions on Geoscience and Remote Sensing. doi:10.1109/TGRS.2020.3042694

Oliver, C., Quegan, S. (2004). Understanding Synthetic Aperture Radar Images. Artech House.

Qiu, F., Berglund, J., Jensen, J.R., Thakkar, P., Ren, D. (2004). Speckle Noise Reduction in SAR Imagery Using a Local Adaptive Median Filter. GIScience Remote Sens. 41, 244–266. doi:10.2747/1548-1603.41.3.244

Santoso, A. W., Pebrianti, D., Bayuaji, L. and Zain, J.M. (2015). Performance of various speckle reduction filters on Synthetic Aperture Radar image. 4th International Conference on Software Engineering and Computer Systems (ICSECS), Kuantan, Malaysia, 2015, pp. 11-14, doi: 10.1109/ICSECS.2015.7333103.

Schmitt, M., Hughes, L. H., Qiu, C., and Zhu, X. X. (2019). SEN12MS – A Curated Dataset Of Georeferenced Multi-spectral Sentinel-1/2 Imagery For Deep Learning and Data Fusion, ISPRS Ann. Photogramm. Remote Sens. Spatial Inf. Sci., IV-2/W7, 153–160 doi:10.5194/isprs-annals-IV-2-W7-153-2019

Sheng, Y. and Z.-G. Xia. (1996). A Comprehensive Evaluation of Filters for Radar Speckle Suppression. Proceedings of the International Geoscience and Remote Sensing Symposium, 27–31 May, 1996, Lincoln, NE, 1559-1561.

Yang, X., Denis, L., Tupin, F., Yang, W. (2019). SAR Image Despeckling Using Pre-trained Convolutional Neural Network Models. 2019 Joint Urban Remote Sensing Event (JURSE). doi:10.1109/jurse.2019.8809023

Zhang, K., Zuo, W., Chen, Y., Meng, D., Zhang, L. (2017). Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. IEEE Transactions on Image Processing, 26(7), 3142-3155. doi:https://doi.org/10.1109/TIP.2017.2662206

Zhang, Q., Yuan, Q., Li, J., Yang, Z., Ma, X. (2018). Learning a Dilated Residual Network for SAR Image Despeckling. arXiv:1709.02898. doi:10.48550/arXiv.1709.02898

Zhang, Q., Sun, R. (2020). SAR Image Despeckling Based on Convolutional Denoising Autoencoder.
arxiv.org/abs/2011.14627v1.
https://doi.org/10.48550/arXiv.2011.14627