194.077 Applied Deep Learning - 2021W

Assignment 1 – Initiate

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Despeckling C-band SAR data using a Deep Residual U-Net

Beat the classics (and later the stars)

1. Introduction

Microwave remote sensing and in particular synthetic aperture radar data is an important input for a wide range of applications. These include environmental monitoring, soil moisture retrieval, flood mapping, yield prediction and many more. In contrast to optical remote sensing, the synthetic aperture radar (SAR) sensor can operate independent from weather conditions and daylight. Thus, it allows gap free measurements and denser time series. However, it also comes with a downside. The interaction of the emitted wave with the surface leads to destructive and constructive interference which results in an inherent noise in the measurement, the so-called speckle effect.

2. State of the art

Current state of the art approaches to remove this noise are based on basic image processing algorithms which average pixel values in a sliding window to reduce the noise. Yet, this averaging come with the costs of a loss of information and a lower resolution. First approaches to use machine learning or in particular deep learning for this application were hindered by the lack of noise free reference data. To overcome this, several study propose to use optical images converted to grey-scale instead [1]. Due to difference in the acquisition and simplified noise model, these datasets often fail to represent the characteristics of real SAR acquisitions.

3. Goal of the project

This project will overcome this obstacle by using the global Sentinel-1 backscatter model (S1GBM) as a (de facto) noise free refence [2]. This data is built by averaging measurement of the Sentinel-1 C band SAR mission over two years on a global scale, leading to an extreme noise reduction. By adding artificial noise to this dataset, we obtain a global training and reference dataset. These datasets will be used to train and evaluate a U-Net for noise reduction. Ideally the trained network can then be used to remove resp. reduce the Speckle noise in single SAR acquisitions.

4. Dataset

Figure 1: Illustration of a noise free SAR image of Vienna on the left and a (original) noisy scene on the right.

The S1GBM is provided in the Equi7 Tiling Grid [3]. In this work, approximately eleven tiles over Europe will be chosen covering different land cover types. Each tile is provided with a ground sampling distance of 10m and persisting of 10,000x10,000 pixels. Thus, each tile covers a ground area of 100km². For simplification, only VV polarized data will be used. To generate pairs of noisy and noise free scenes, the speckle model proposed by Singh, P. & Pandey R. S. [4] will be applied to the S1GBM data. The here proposed formula will be extended by a noise level factor, to introduce the noise level dependency of the landcover. The variable will be determined by the standard deviation of each pixel derived from two years of measurement (also part of the S1GBm dataset). To feed this data to the network a tiling workflow will be created, splitting each tile into patches of 500x500 pixels. The patches of ten of these tiles will be randomly split into 80% training and 20% validation data. The entire 11th tile will be used for testing in order to get a large scale impression of the model output.

5. Methodology

The U-Net architecture was originally proposed by Ronneberger et al. [5] as a semantic image segmentation network. In recent years, several studies also used the architecture for image denoising with the extension of residual blocks [6,7]. A recent study indicates the good performances of this architecture to remove gaussian noise from various image types [8]. Thus, indicating also the suitability to remove Speckle noise from SAR images. However, to the best of my knowledge, the application of a U-Net for SAR images despeckling has not yet been investigated.

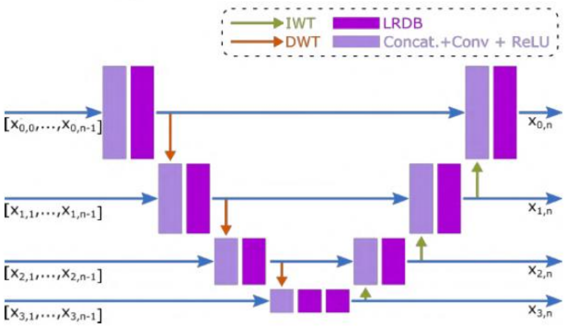

Figure 2: Illustration of a U-Net using local residual dense blocks (LRDB).

6. Evaluation

After the network is trained, it will be tested on the eleventh (unseen) tile with simulated noise and single SAR acquisitions. Given the limited amount of time and the lack of ground truth for the originally SAR image, the evaluation of the results will be purely based on the visual comparison. Hereby, the obtained despeckled images will be compared with the same images despeckled with the current state-of-the art Lee filter. Although this is not an objective measurement, it allows a good impression if the proposed method is able to remove the speckle and achieves comparable or better results than a current state-pf-the art approach.

7. Application

Commonly, speckle filters are applied in the processing chains that prepare SAR images to be analyze ready for the user. A lot of these workflows are implemented in python. Therefore, in a last step, a python function will be developed, that allows the simple implementation of the developed model in a workflow. The function will take an entire SAR scene as an input, split it up in patches of the same size of 500x500 pixels and apply on these the despeckle model. Afterwards, it will reconstruct the image out of the patches, georeference it and write it to a new file.

Bibliograhpy

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Work and time schedule

Task	Expected hours	CW 42	CW 43	CW 44	CW 45	CW 46	CW 47	CW 48	CW 49	CW 50	CW 51	CW 52	CW 1	CW 2	CW 3
Assignment 1	5														
Literature Review	5														
Assignment 2	5														
Write Python Script to simulate speckle noise	10														
Create Data sets	5														
Set-up Model in Python	25														
Train Model	10														
Test/evaluate/update Model	10														
Assignment 3	5														
Write Python Script to allow predictions of entire Sentinel-1 scenes (aka application)	15														
Prepare final presentation	5														
Total	**100**														