COMPARISON OF SAR IMAGE DESPECKLING FILTER PERFORMANCE FOR DIFFERENT ENVIRONMENTS

INTRODUCTION

Synthetic Aperture Radar (SAR) is a remote sensing technique capable of imaging large regions. **Speckle** is a type of **granular noise** that greatly deteriorates the quality of images produced by SAR. Though the exact patterns may be random, the **properties of the surface** or target being imaged affect the **characteristics of the speckle**. Therefore, there are **different optimal despeckling filters** for different types of surfaces.

Clean Speckled
Taken from scikit-image

OBJECTIVE

To empirically assess and identify **optimal despeckling methods** for various surface types. By **comparing** and **analysing** the performance of common despeckling techniques across a range of surfaces, we aim to determine the most **effective filters** for enhancing the interpretability of SAR data.

HYPOTHESIS

We hypothesised that landscapes with **different surface properties** would be despeckled to **different extents** by the same filters. For these experiments, we proposed that terrain can be grouped into **three main types** for faster analysis: urban, maritime and rural.

	Urban	Maritime	Rural
Scatterers	Buildings, ground (concrete, grass)	Water, ships	Vegetation, ground (clay, soil, snow etc.)
Aim of filter	Preserving fine details of closely-packed structures	Preserving isolated point targets (ships) on a highly homogenous surface	Preserving topological information about the surface

METRICS

Performance metric	Best at detecting
Equivalent Number of Looks	Speckle reduction
Mean square error	Pixel-wise discrepancies
Structure Similarity Index Metric	Structural similarity
Signal to noise ratio	Noise levels in relation to the object of detection
Peak signal to noise ratio	

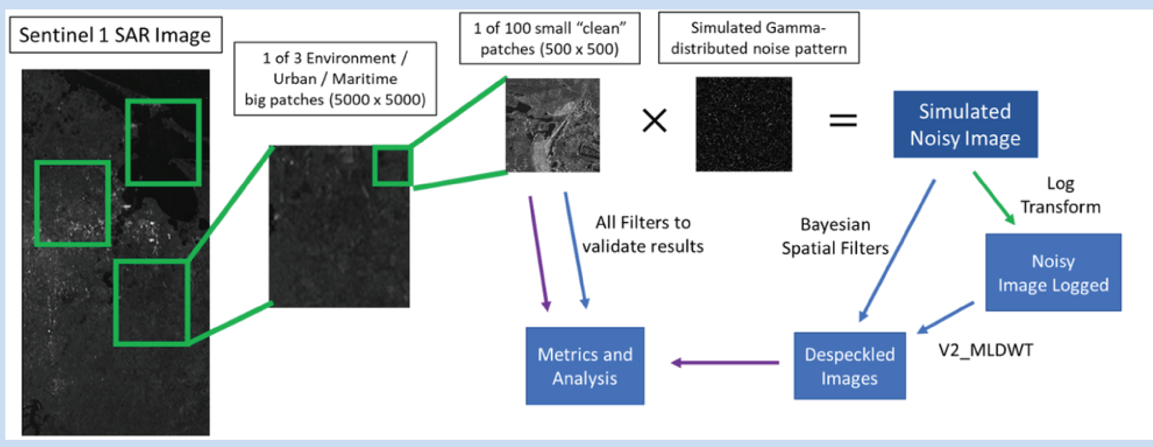
METHODOLOGY

Download SAR dataset and crop 100 small patches of 500×500 pixels each for the three categories of terrain: urban, maritime and rural.

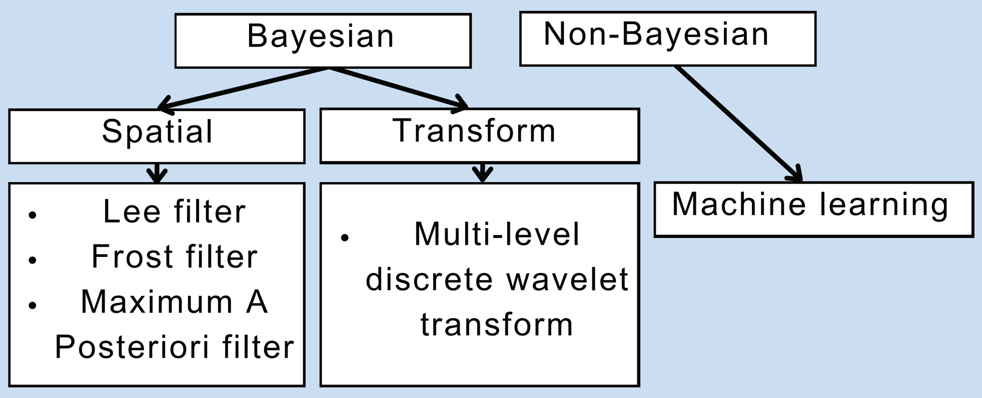
Create simulated SAR images with added Gamma-distributed noise to make a clean-noisy image pair.

Test the filters on the simulated images, and apply all metrics to get the performance of the filters on the simulated images. Use the results to estimate what the results will be like on real SAR images.

Test the filters on the original Sentinel 1 images, and similarly apply metrics to measure their performance. Analyse the results.



FILTERS



DATASET

Simulated images were necessary in order to **apply metrics** which all require a clean "**ground truth**" image for the filtered resultant image to be compared to. Actual SAR data is necessary to **validate** the **robustness** of the filtering approaches to real, **random** speckle patterns.

RESULTS

SIMULATED DATA

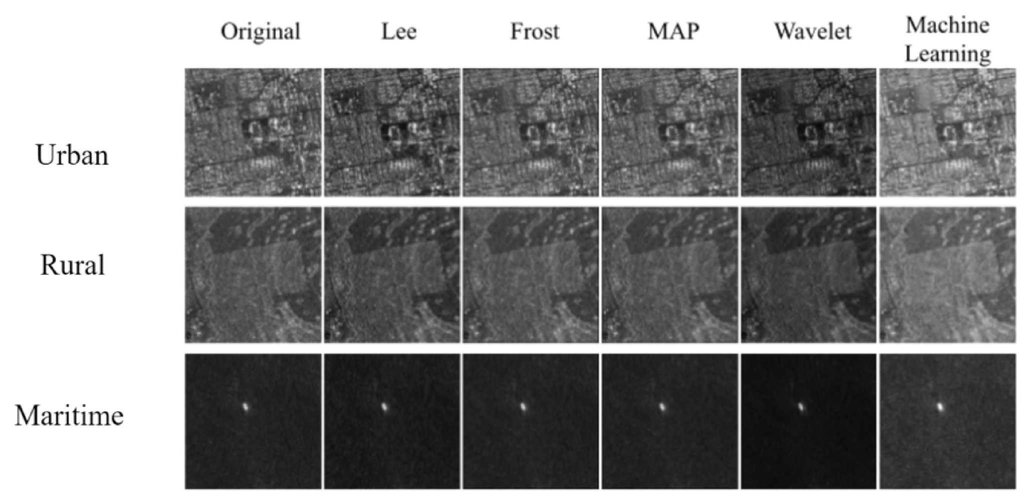
Surface type / Filter		Noisy	Lee	Frost	MAP	Wavelet	Machine Learning
Urban	PSNR	18.0	**19.8**	19.2	18.7	18.4	19.7
	SNR	0.443	**5.9**	4.93	4.58	4.56	5.79
	MSE	2440	**722**	1390	1570	952	977
	ENL	3.65	5.76	7.99	7.59	**13.1**	6.35
	SSIM	0.628	**0.678**	0.591	0.565	0.417	0.566

Surface type / Filter		Noisy	Lee	Frost	MAP	Wavelet	Machine Learning
Maritime	PSNR	20.3	24.5	25.3	25.7	25.9	**28.6**
	SNR	-6.60	-1.92	-1.06	-0.655	-0.508	**2.13**
	MSE	680	234	192	176	170	**92.2**
	ENL	2.89	7.52	10.7	14.7	**34.0**	31.8
	SSIM	0.365	0.521	**0.561**	0.519	0.340	0.480

Surface type / Filter		Noisy	Lee	Frost	MAP	Wavelet	Machine Learning
Rural	PSNR	17.8	21.1	21.1	20.8	20.8	**22.3**
	SNR	-3.16	2.05	2.03	1.76	1.69	**3.51**
	MSE	180	503	507	540	549	**391**
	ENL	4.49	9.97	15.6	14.9	**43.9**	15.1
	SSIM	0.487	**0.599**	0.544	0.514	0.301	0.472

REAL DATA

Surface type / Filter		Lee	Frost	MAP	Wavelet	Machine Learning
Urban	ENL	4.69	6.17	5.78	**7.32**	6.35
Maritime	ENL	14.2	20.8	18.3	**40.4**	31.8
Rural	ENL	9.79	13.2	12.1	**19.0**	16.6



DISCUSSION

For urban images, the Lee filter **outperformed** all other filters by a significant margin. While the Lee filter **suppressed speckle**, it did so while **blurring** the image, which was **not ideal**. However, upon visual inspection, it was found that the Lee filter's simple formula allowed it to apply the **least amount of blurring** and **preserve the most amount of similarity** where other filters overcompensated.

For the maritime and rural categories with simulated noise, SAR-CNN had performed relatively well, but **did not preserve image similarity** (SSIM) as well as its counterparts. Lee on the other hand had **poor metrics** but preserved **image similarity better**, possibly due to the greater proportion of **homogenous regions** like the farmland and water that Lee is better suited for.

The wavelet filter was one of the **worst performing**, often blurring out the images entirely. This can be attributed to the **relatively small size** of the images used (500×500 pixels), resulting in fewer coefficients after decomposition. Internal testing showed that the wavelet filter performs **significantly better** when given input images with **larger dimensions**. On the contrary, it is actually the best when tested on the real data in terms of ENL. This is because it tends to darken the image, lowering the standard deviation of the pixels in the image and resulting in a lower ENL. This is also the reason why it has the highest ENL in simulated data too.

CONCLUSION

In conclusion, we recommend the Lee filter for urban terrain and the ML filter for maritime and rural terrain based on the simulated data. The results from real data are inconclusive because we could only use ENL and the wavelet filter was much better at that metric than the other filters.

REFERENCES

The images used in the Real Data were cropped from a Sentinel-1 dataset taken from NASA Earthdata. All other images, figures, and graphs were self-drawn.

Members:
Christina Pan Wan Ting, Raffles Girls' School
Ng Zi Yang, Temasek Junior College
Terrence Lin Junyong, Raffles Institution
Mentors:
Felicia Tai, DSO National Laboratories
Alastair Wee, DSO National Laboratories