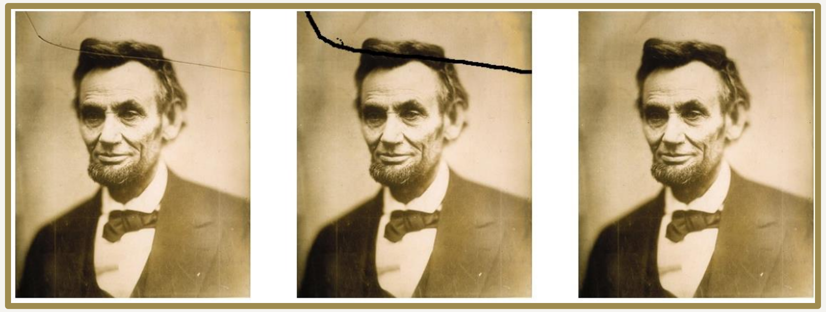
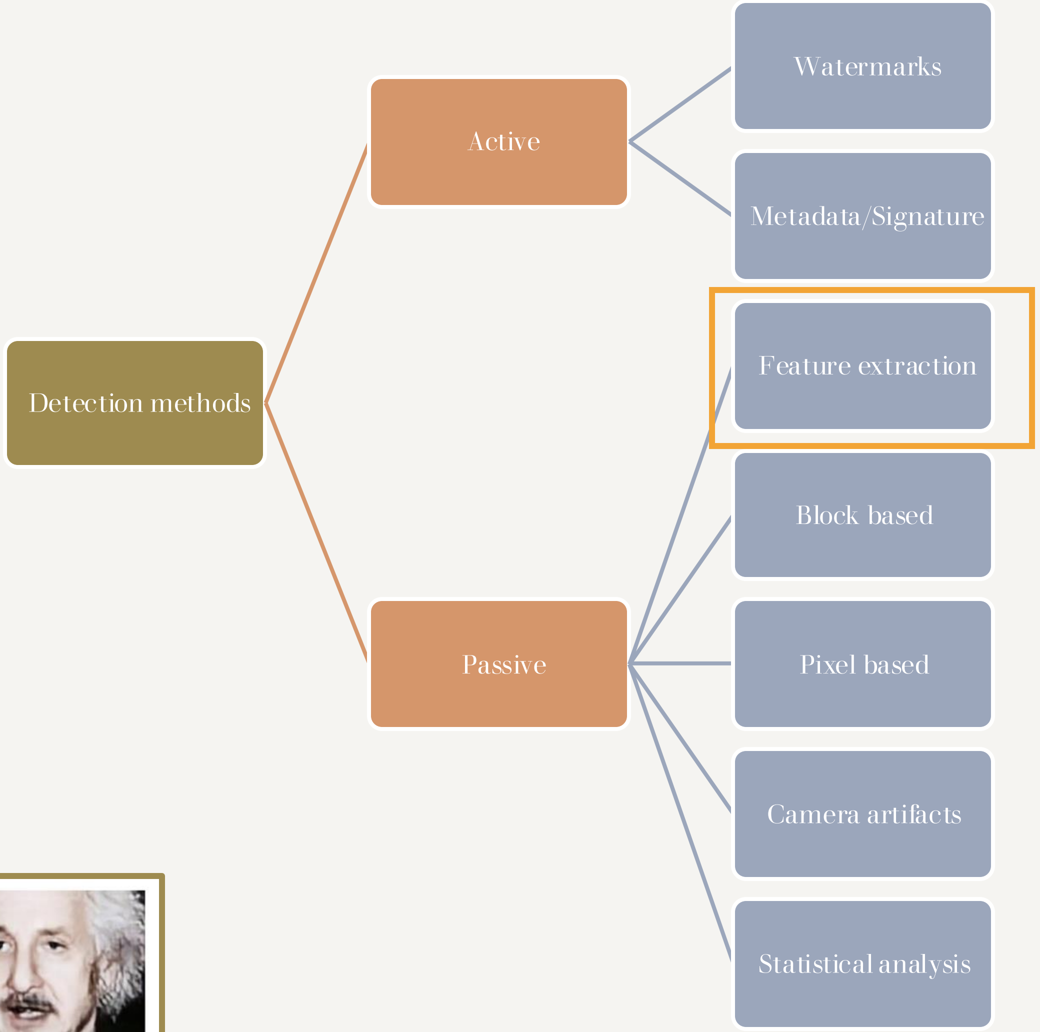
Inpainting Detection Using Wavelet-Based Features

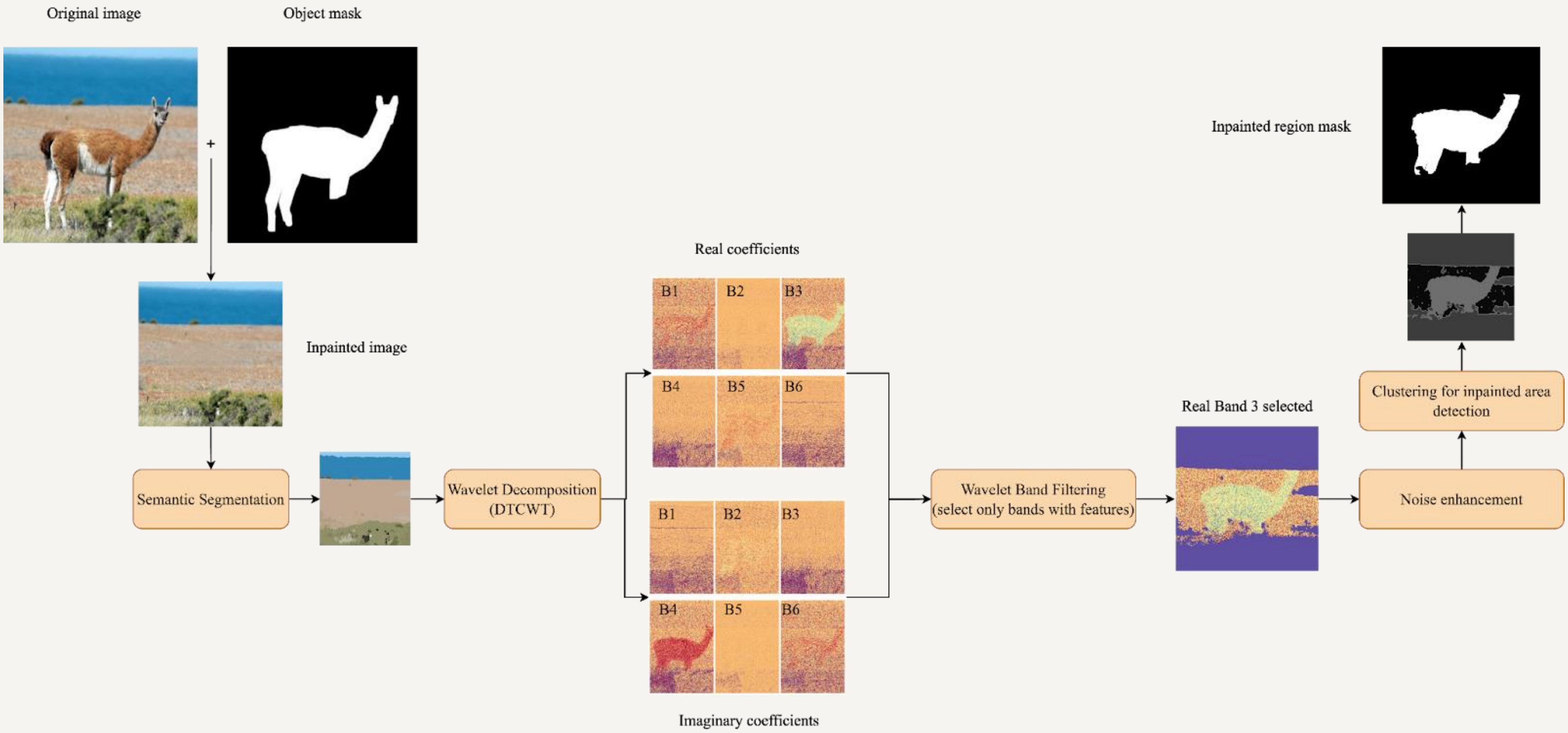
SHARVARI DESHMUKH, NIKHIL GANDUDI SURESH, AVANTI BHANDARKAR

Overview of the Field





Prior Work: Implementation by Barglazan and Brad [1][3]

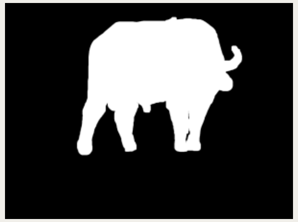
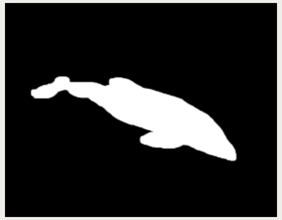
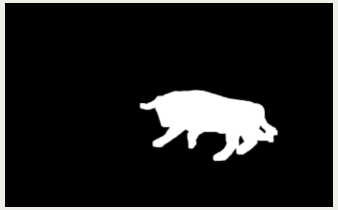


IMAGES IN THE FLOWCHART ARE FROM [1]
NOISE ENHANCEMENT METHOD IS IMPLEMENTED ACCORDING TO [2]

Challenges & Shortcomings

- Image Segmentation – Hierarchical Feature Selection
- Selection of correct wavelet bands
- Choice of optimal filter
- Selection of clusters based on noise variance
- Morphological operations to get the final mask

Our Dataset

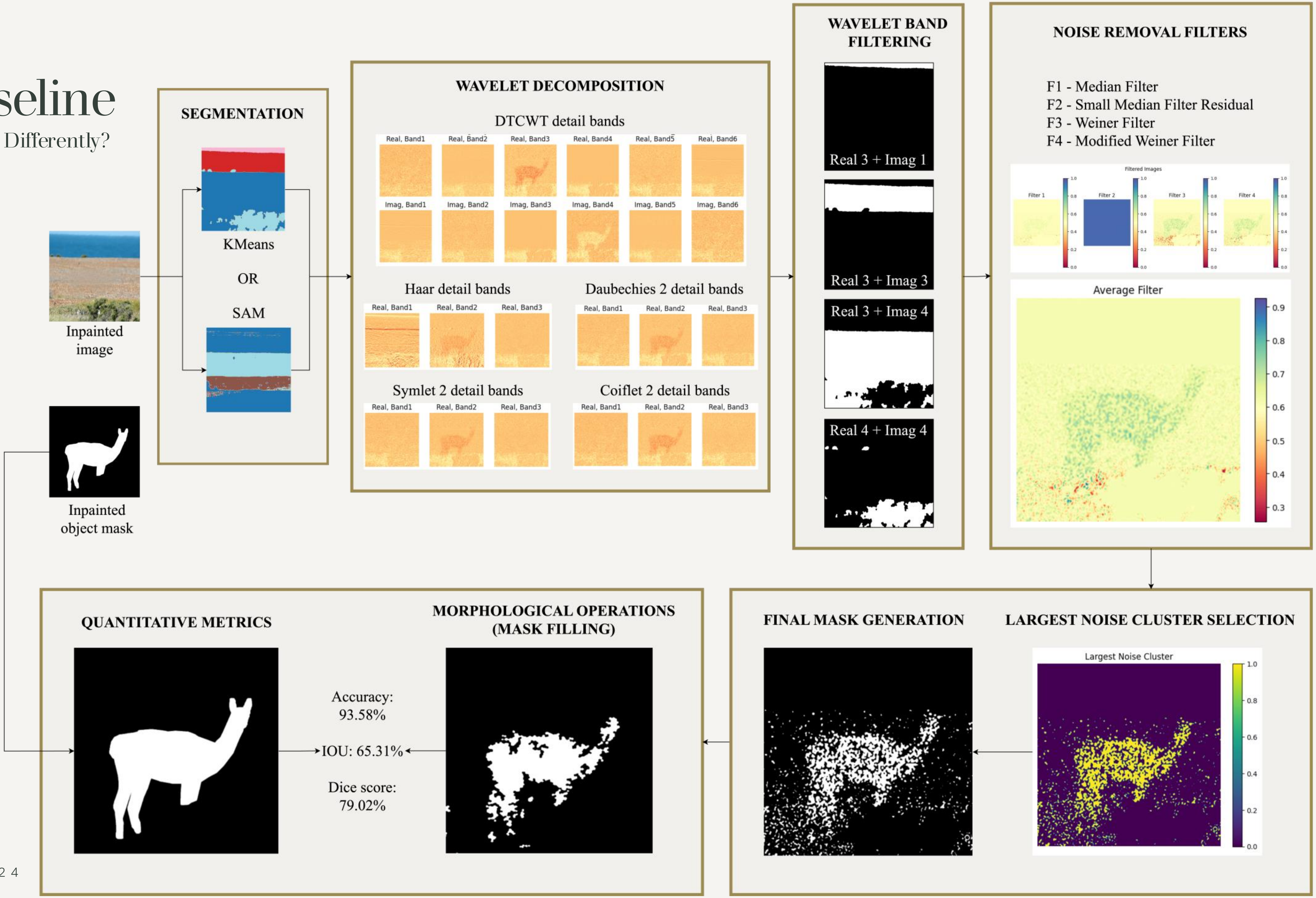
Image Properties	Blurred Image	Smooth Background	Textured Background	Patterns	Natural Scenes
Sample Image					
Mask					

Inpainting Methods

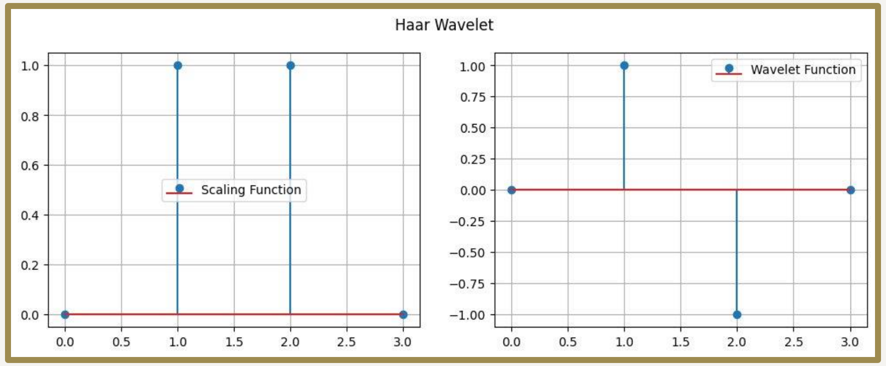
Original Image	MAT	LAMA	Samsung AI
			
			
			
			

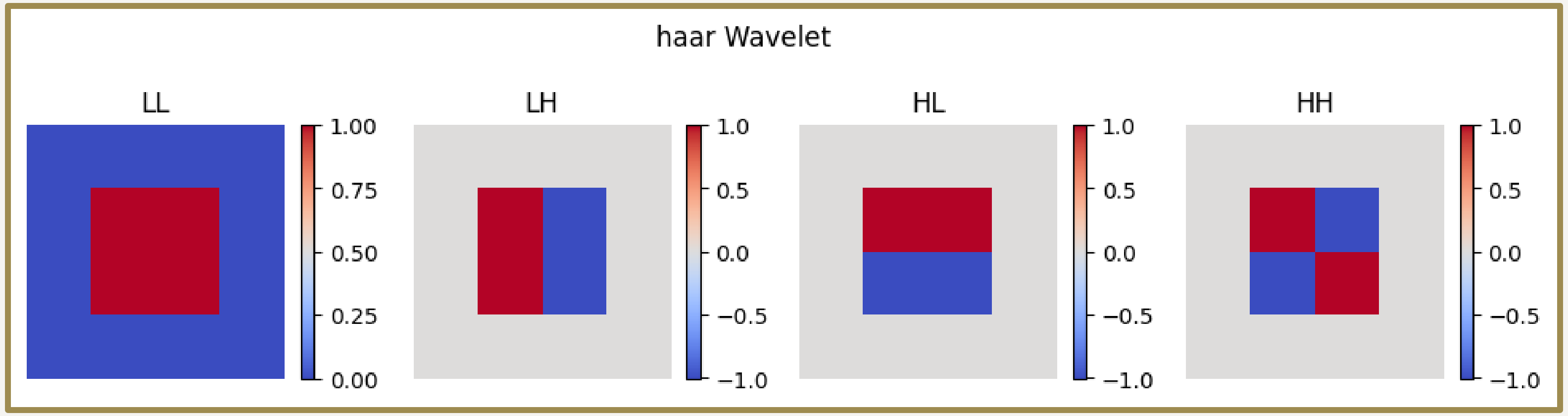
Our Baseline

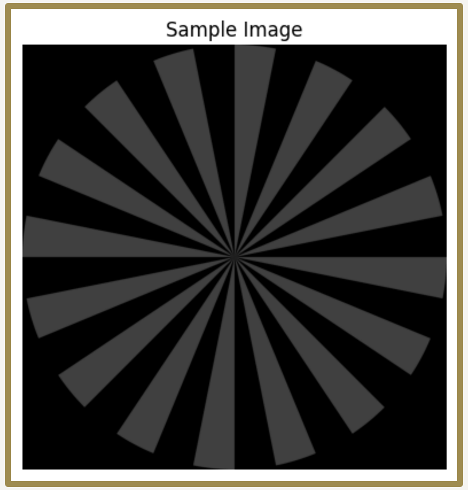
What Did We Do Differently?

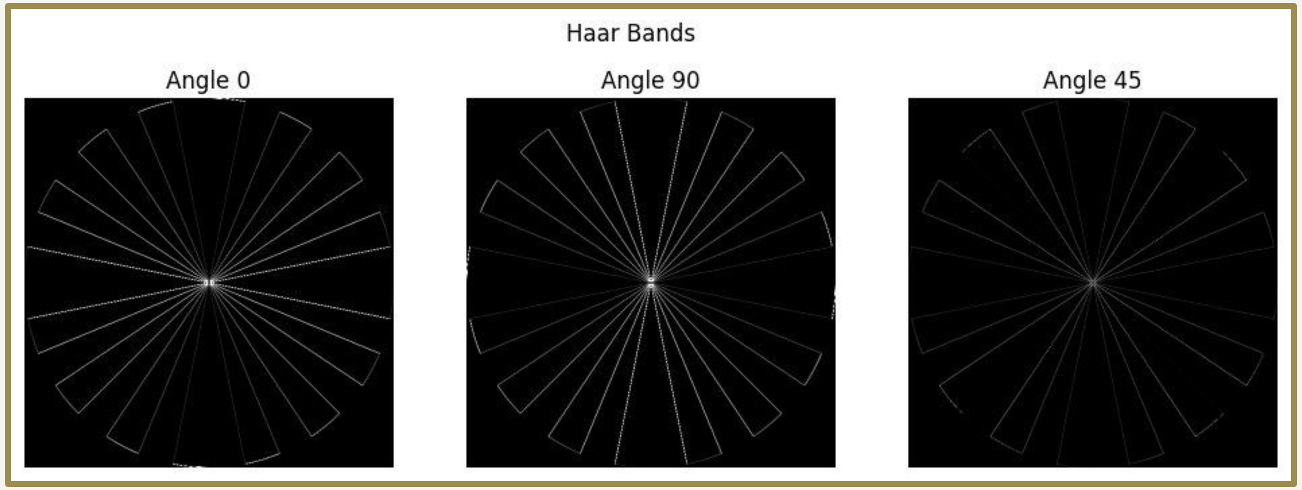


Primer on Wavelets - Haar



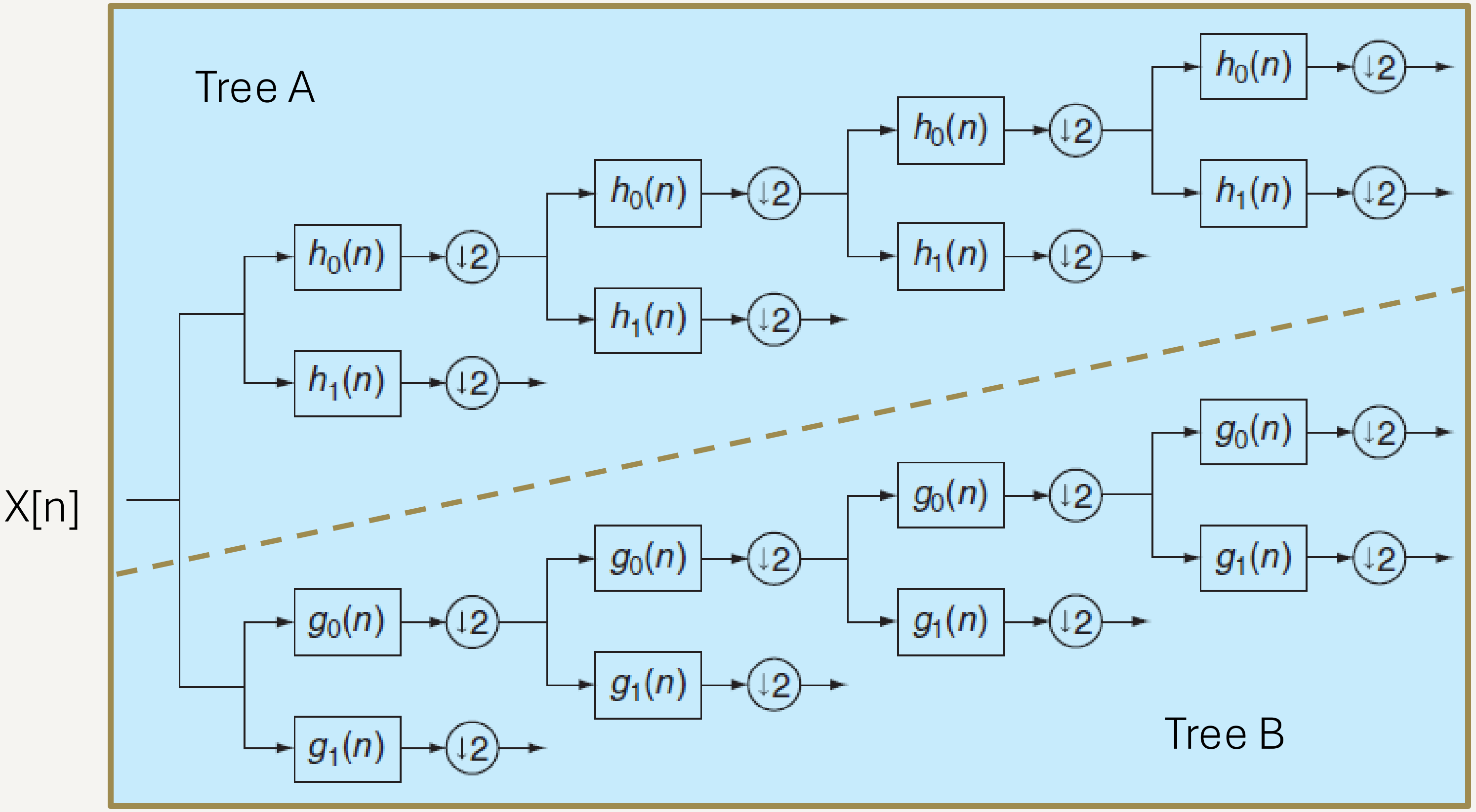






Introducing DTCWT

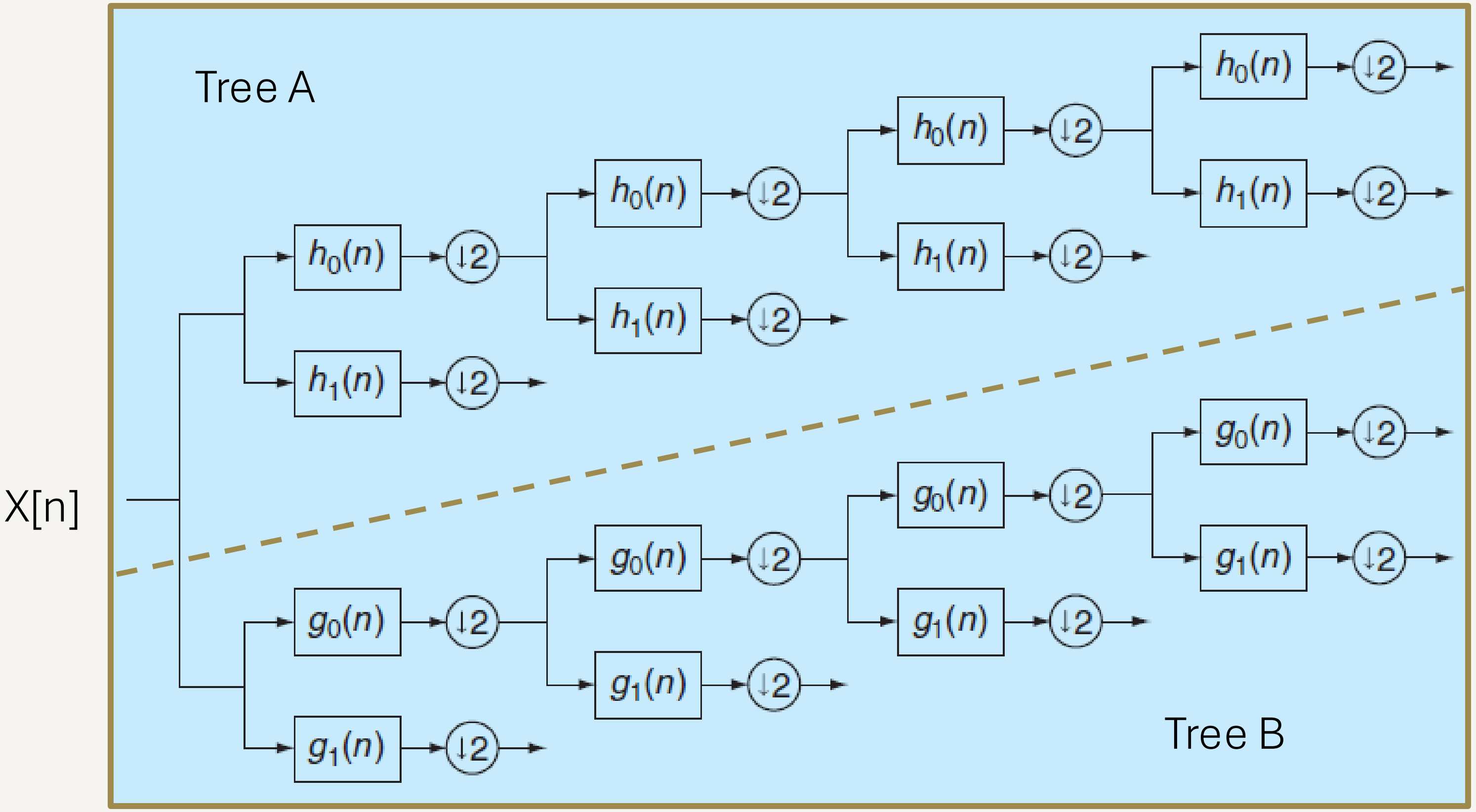
Dual-Tree Complex Wavelet Transform



Dual-Tree

Introducing DTCWT

Dual-Tree Complex Wavelet Transform



Dual-Tree

Complex Wavelet

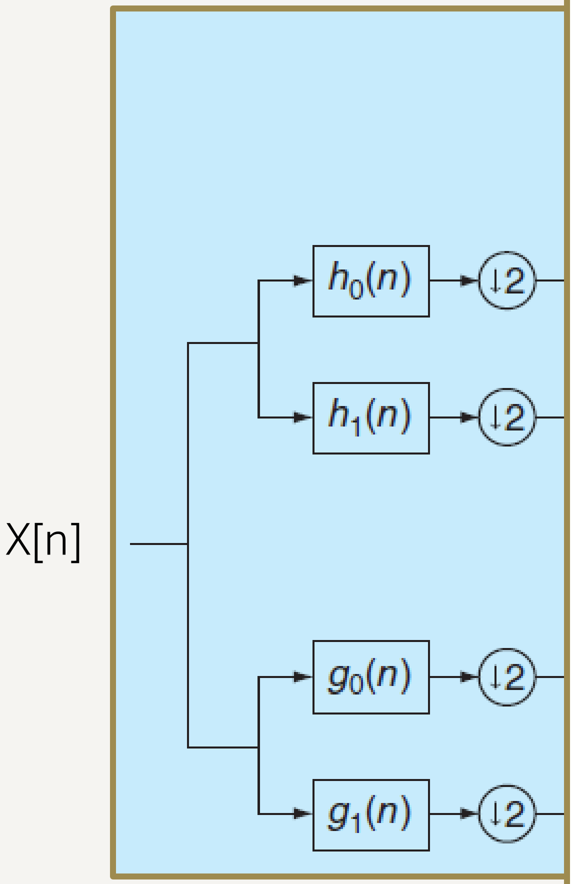
$$\psi(x) = \psi_h(x) + j\psi_g(x)$$

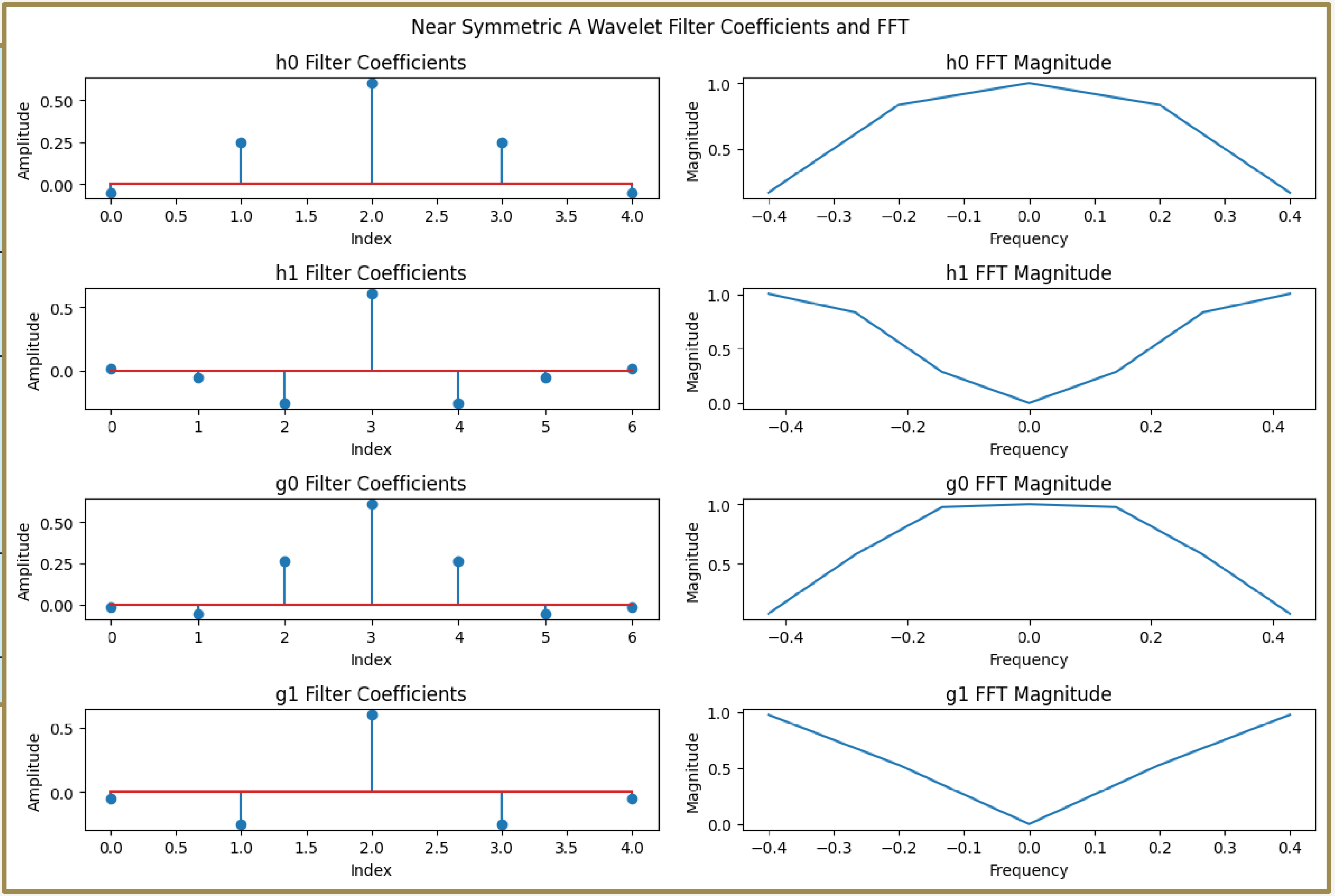
$$\psi(y) = \psi_h(y) + j\psi_g(y)$$

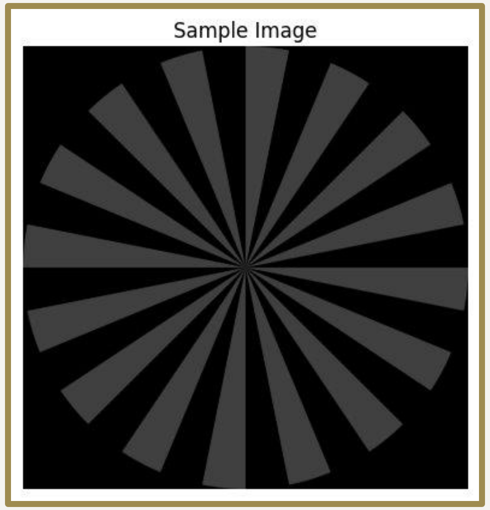
$$\phi(x) = \phi_h(x) + j\phi_g(x)$$

$$\phi(y) = \phi_h(y) + j\phi_g(y)$$

DUAL-TREE DIAGRAM FROM [4]
GENERAL INFORMATION ABOUT DTCWT FROM [5]


X[n]
$h_0(n)$
$h_1(n)$
$g_0(n)$
$g_1(n)$
↓2
↓2
↓2
↓2


Near Symmetric A Wavelet Filter Coefficients and FFT
h0 Filter Coefficients
h0 FFT Magnitude
h1 Filter Coefficients
h1 FFT Magnitude
g0 Filter Coefficients
g0 FFT Magnitude
g1 Filter Coefficients
g1 FFT Magnitude
Amplitude
Index
Magnitude
Frequency



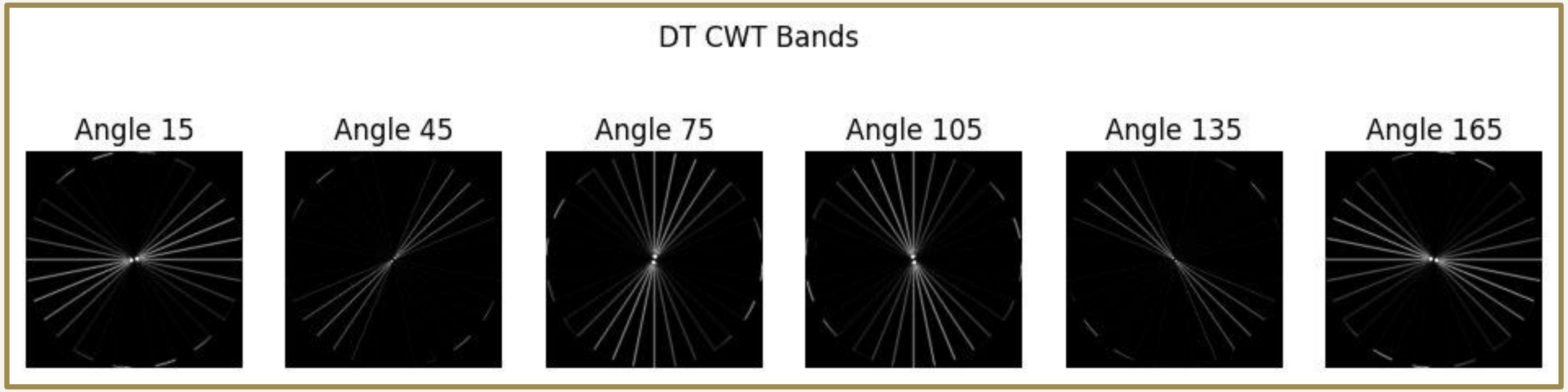
$$\psi_i(x,y) = \frac{1}{\sqrt{2}}\left[\psi_{1,i}(x,y) - \psi_{2,i}(x,y)\right]$$

$$\psi_{i+3}(x,y) = \frac{1}{\sqrt{2}}\left[\psi_{1,i}(x,y) + \psi_{2,i}(x,y)\right]$$

$$\psi_{1,1} = \phi_h(x)\psi_h(y) \qquad \psi_{2,1} = \phi_g(x)\psi_g(y)$$

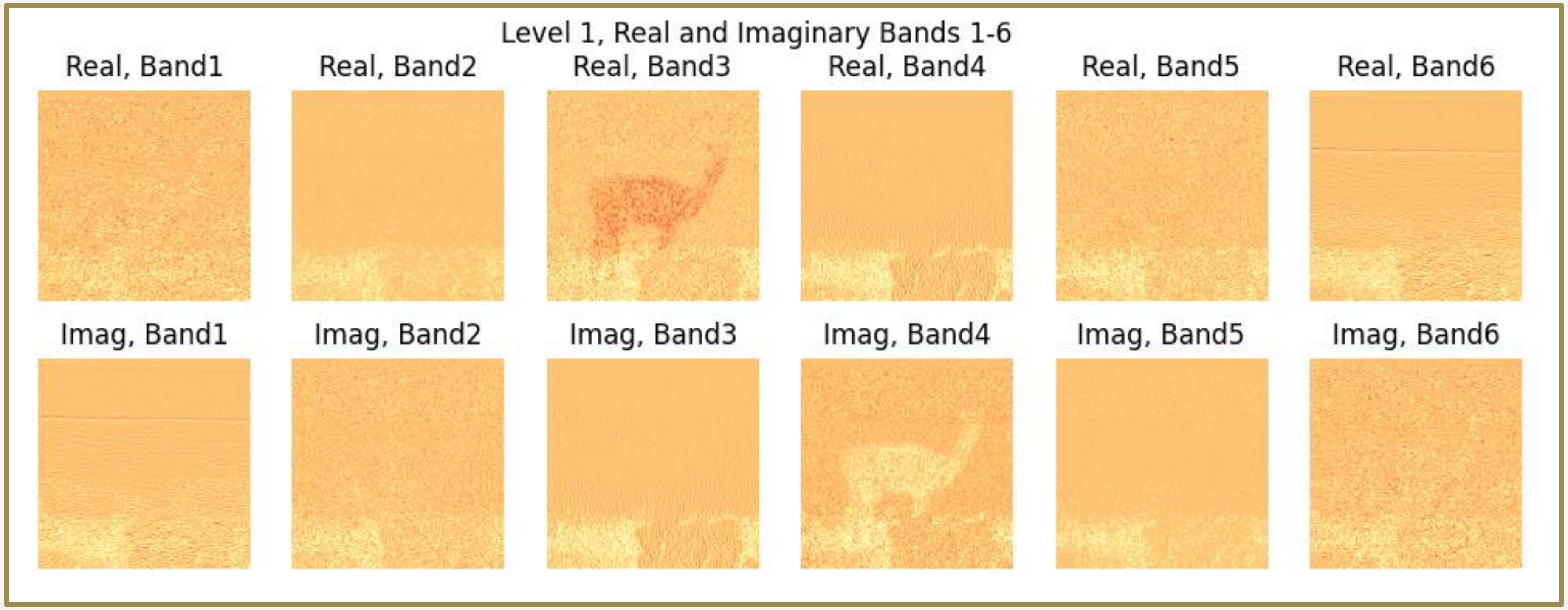
$$\psi_{1,2} = \psi_h(x)\phi_h(y) \qquad \psi_{2,2} = \psi_g(x)\phi_g(y)$$

$$\psi_{1,3} = \psi_h(x)\psi_h(y) \qquad \psi_{2,3} = \psi_g(x)\psi_g(y)$$



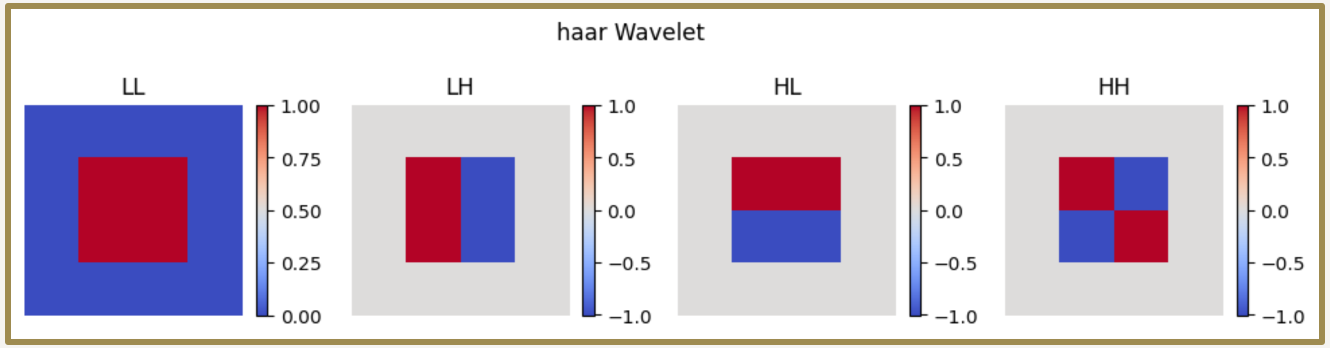
Experiments – Wavelet Transforms

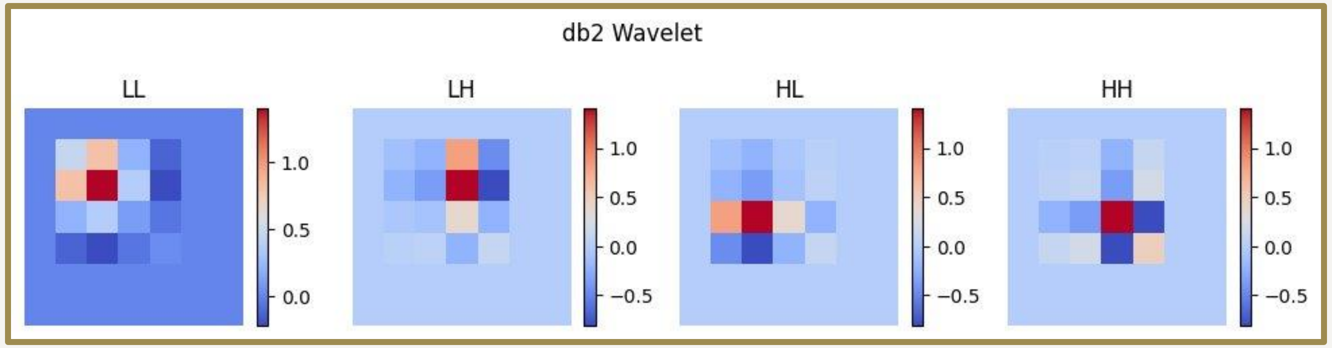
DTCWT



Experiments – Wavelet Transforms

Haar

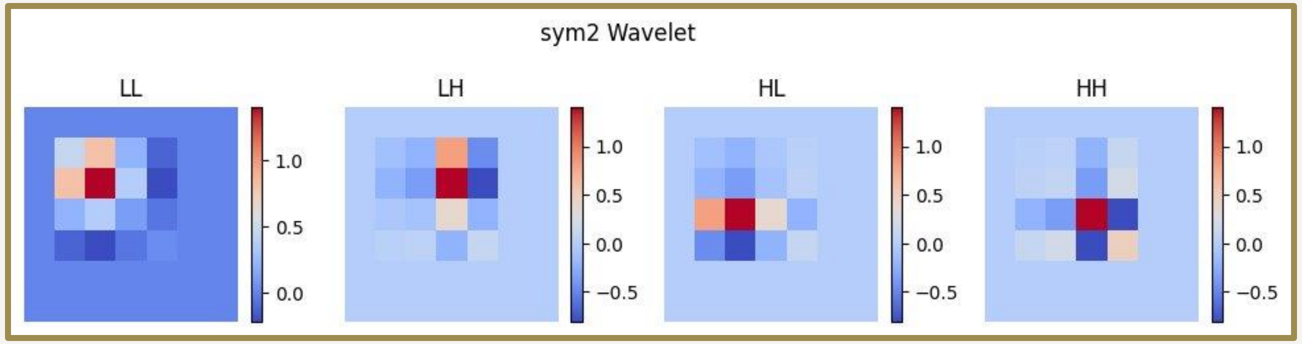


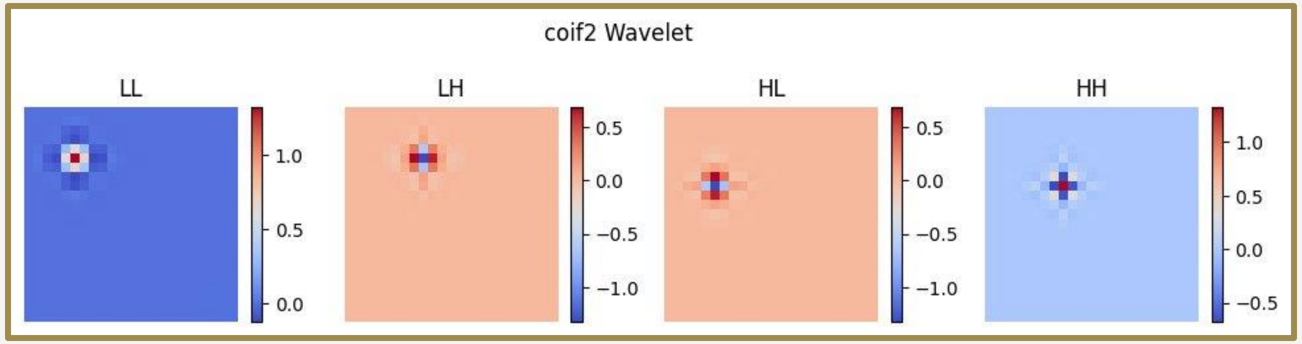


Db2

Experiments – Wavelet Transforms

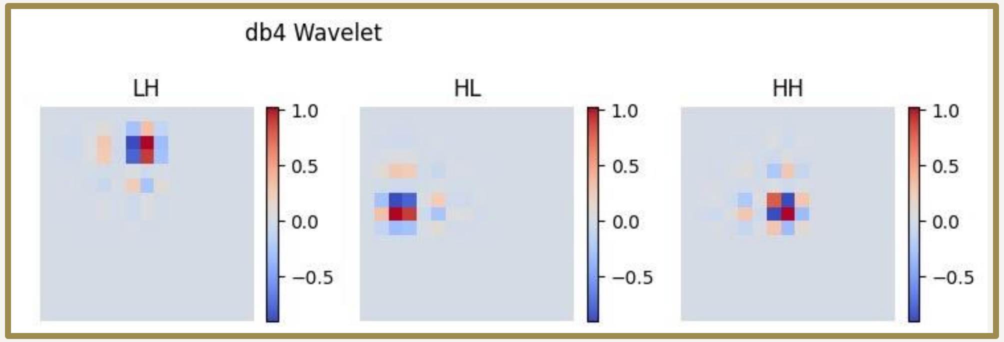
Sym2

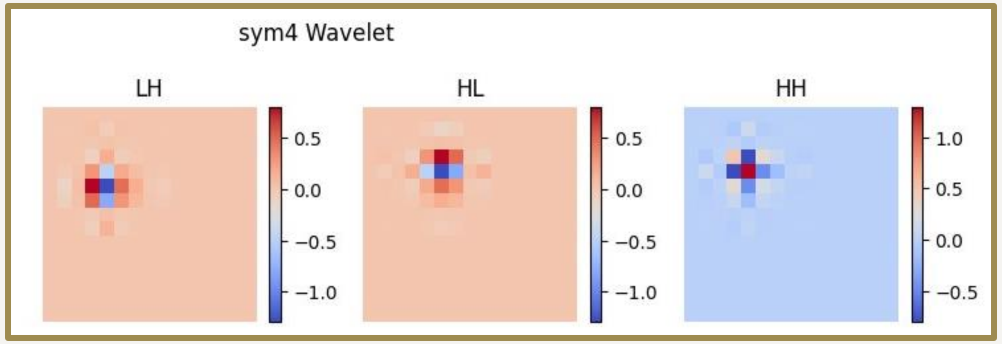


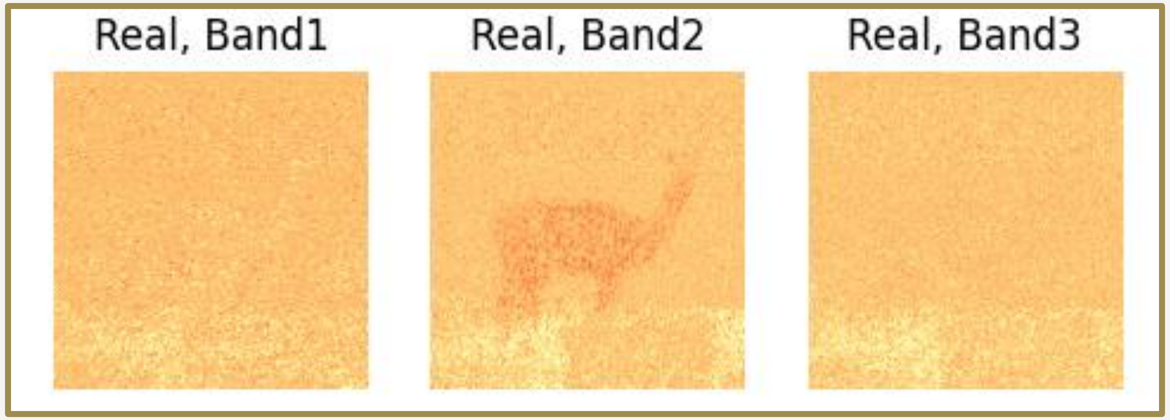


Coif2

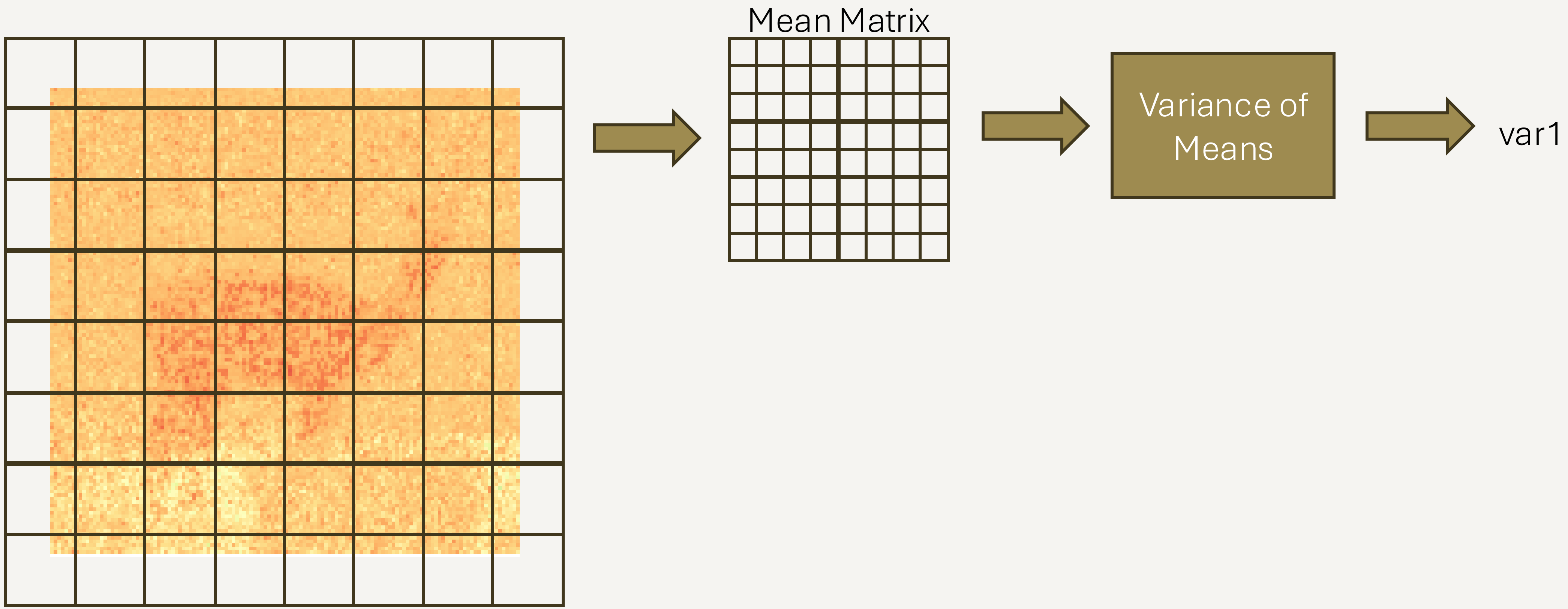
Higher Order Wavelets – Not Very Different Results



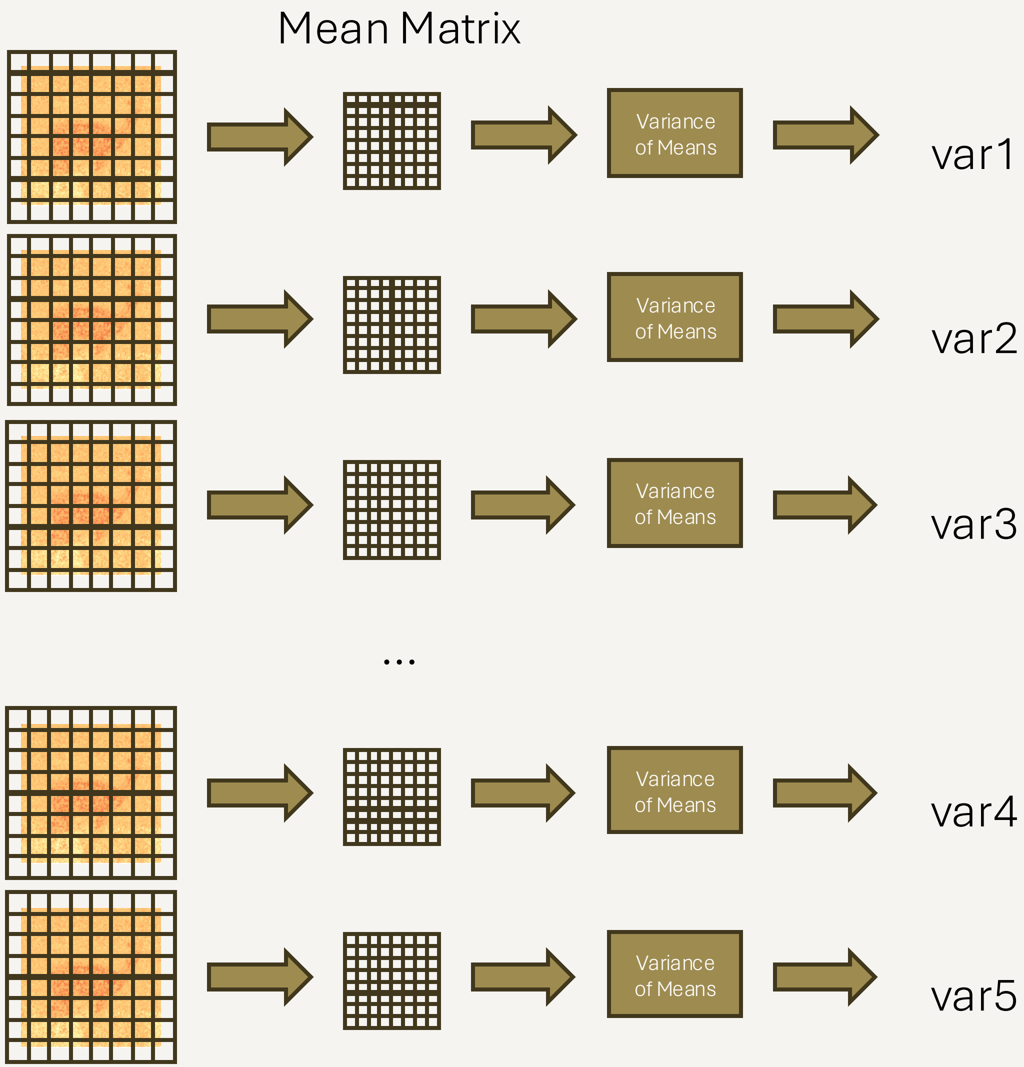




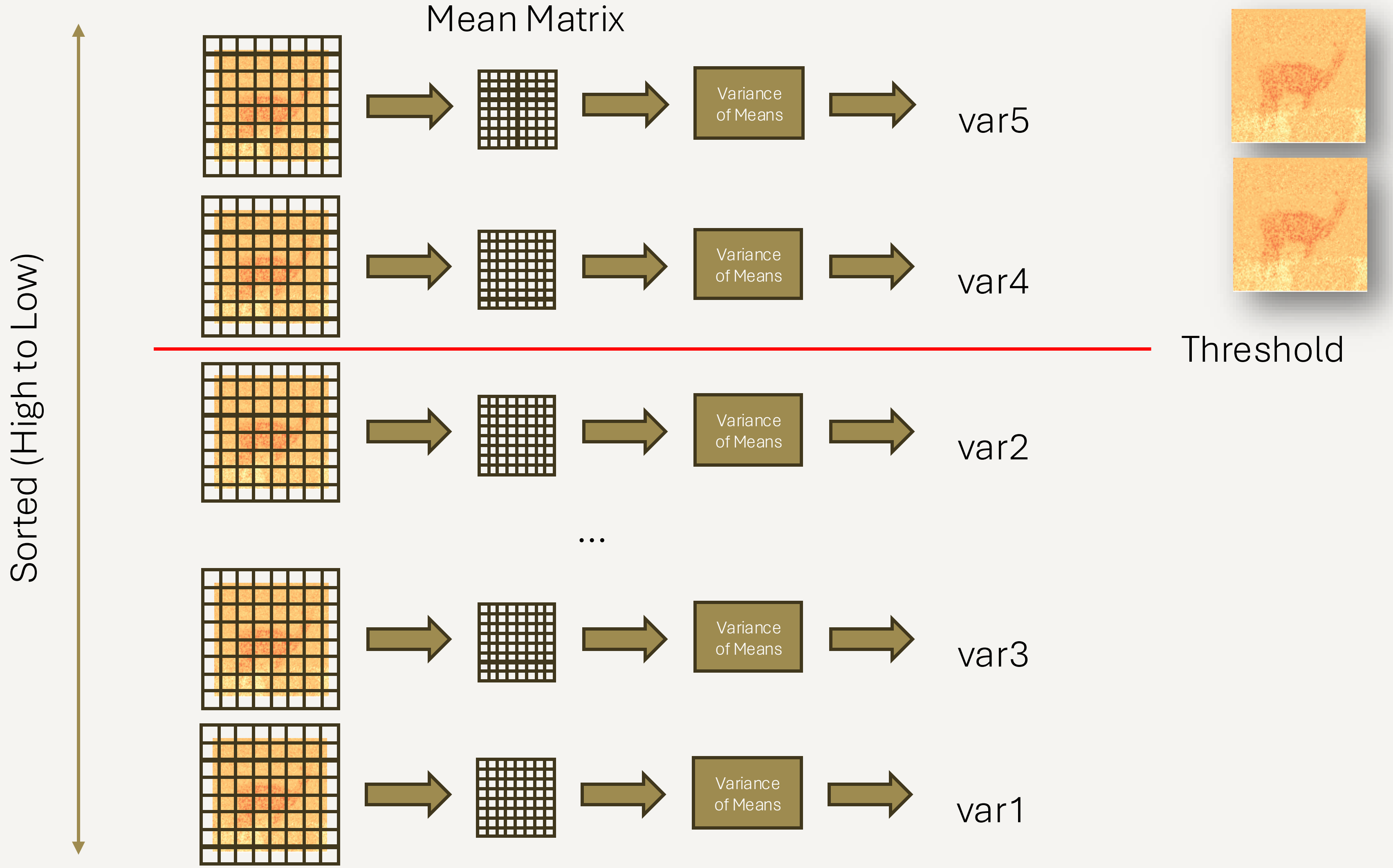
Choosing the Relevant Bands



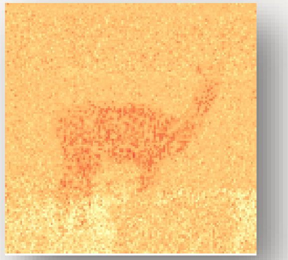
Choosing the Relevant Bands

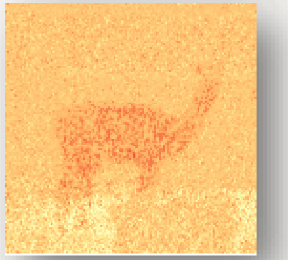


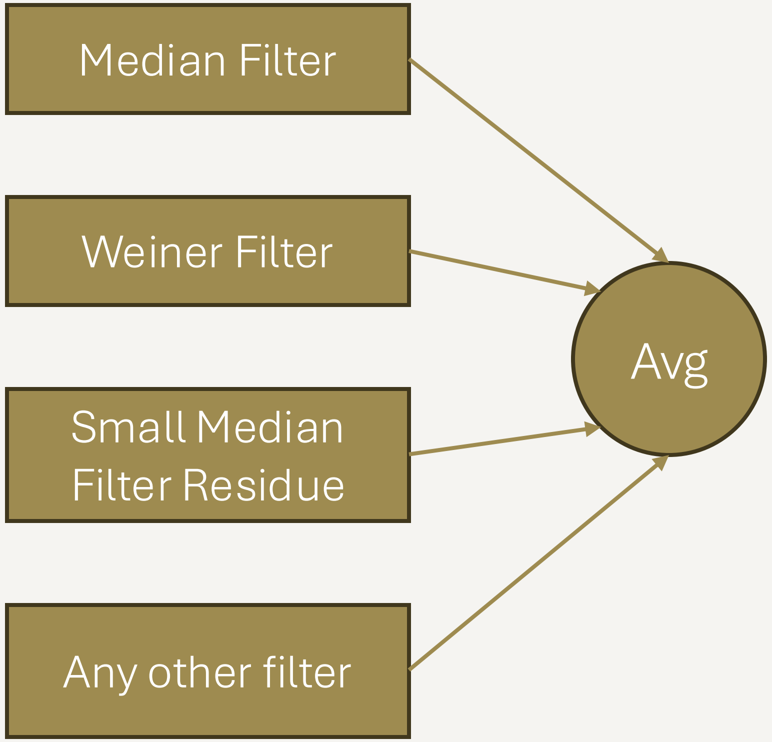
Choosing the Relevant Bands

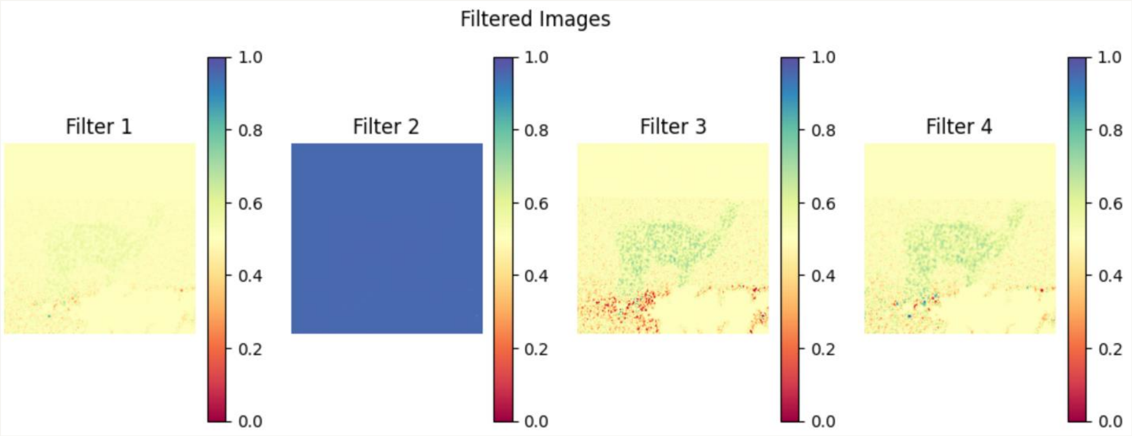


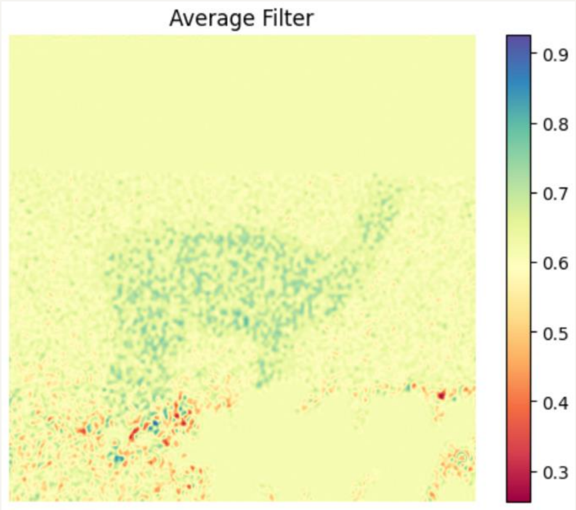
Processing the Relevant Bands



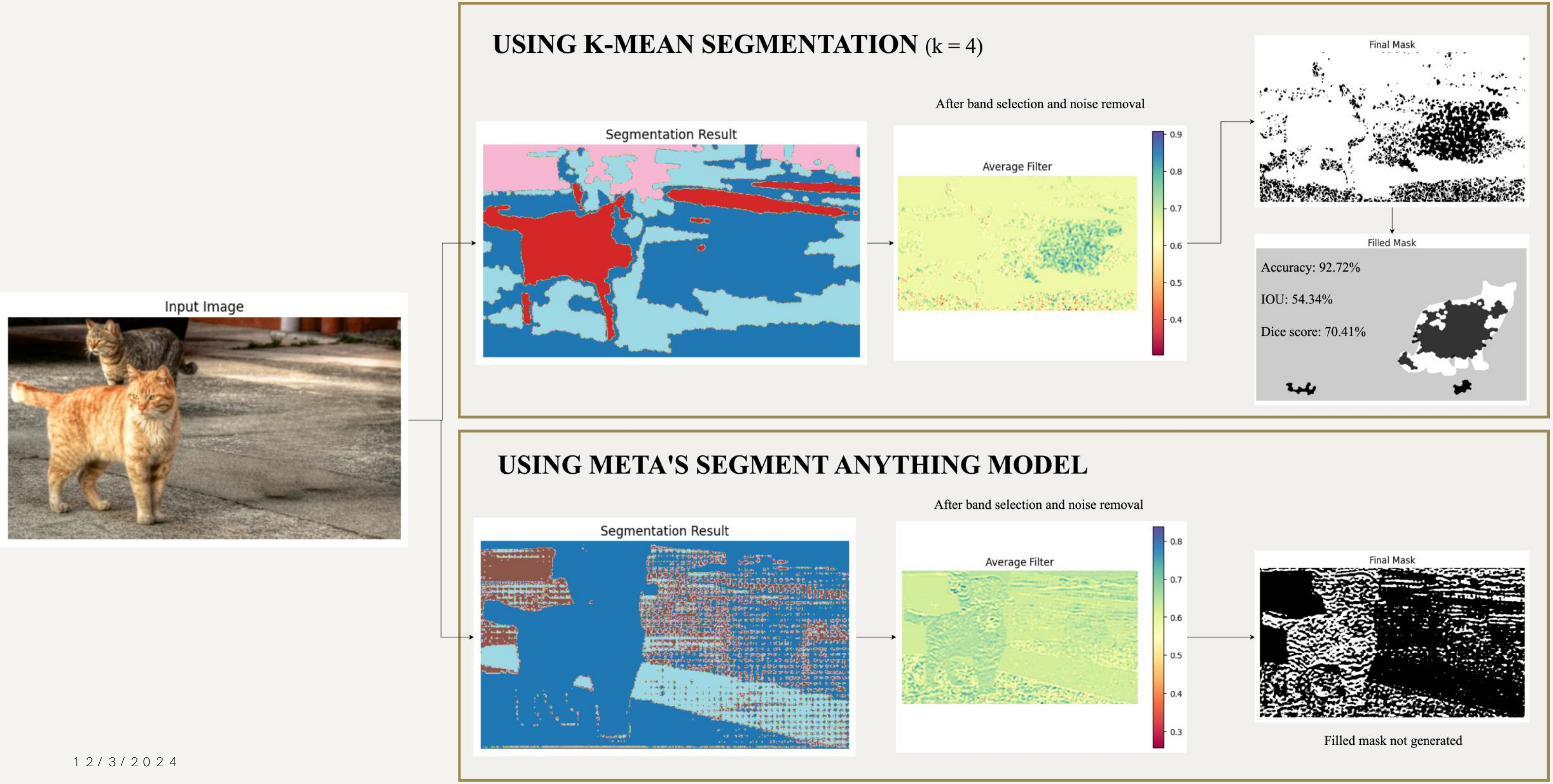








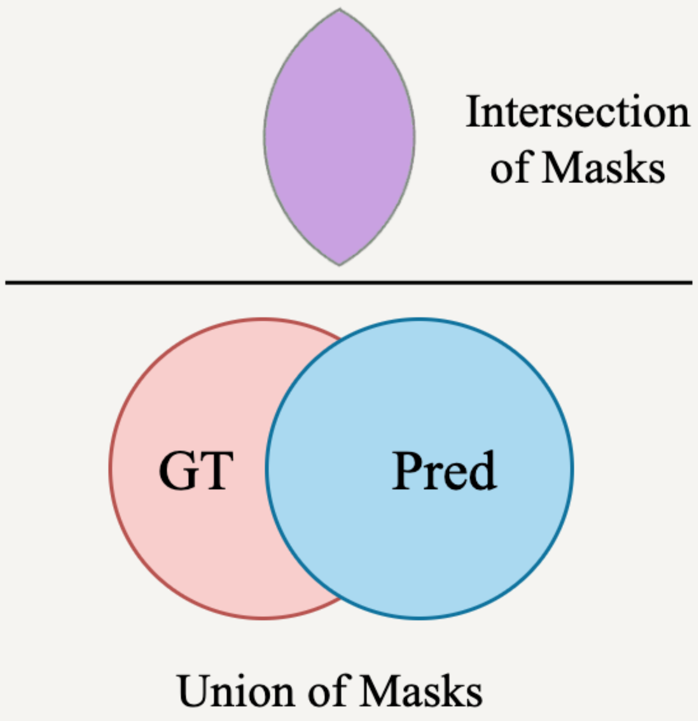
Experiments – Image Segmentation



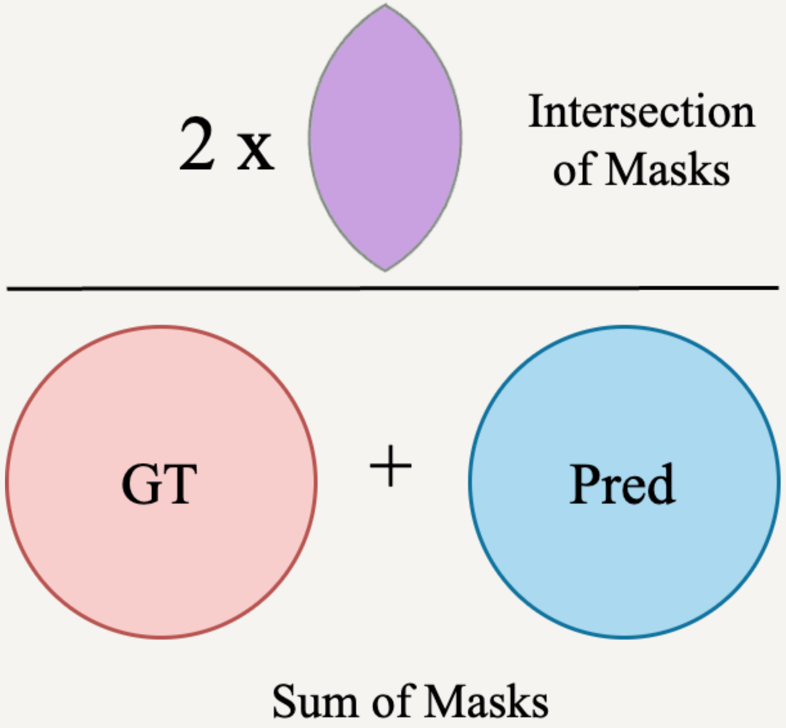
Quantitative Metrics

$$\boxed{\text{Accuracy}} = \frac{\text{Number of Correct Pixels}}{\text{Total Number of Pixels}}$$

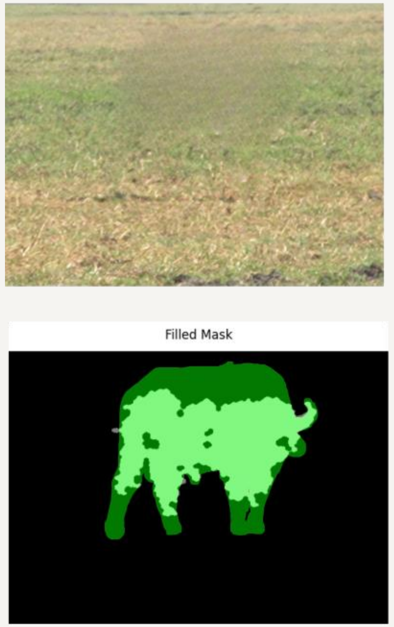
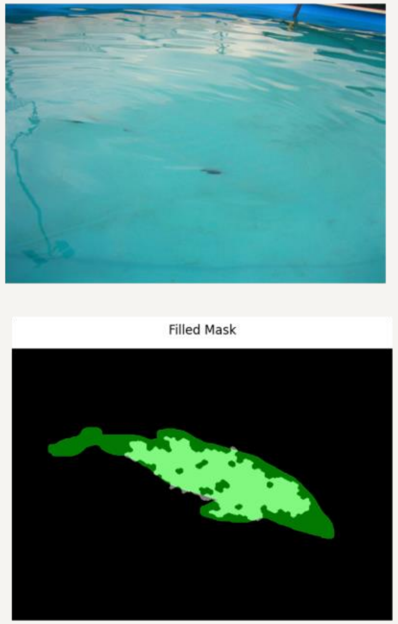
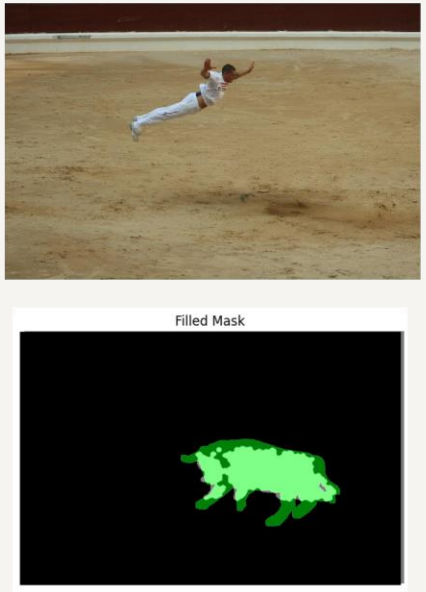
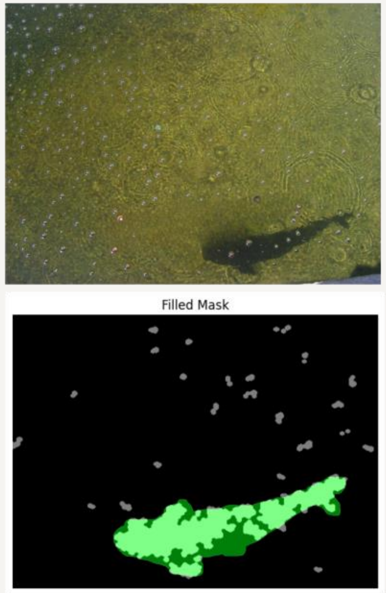
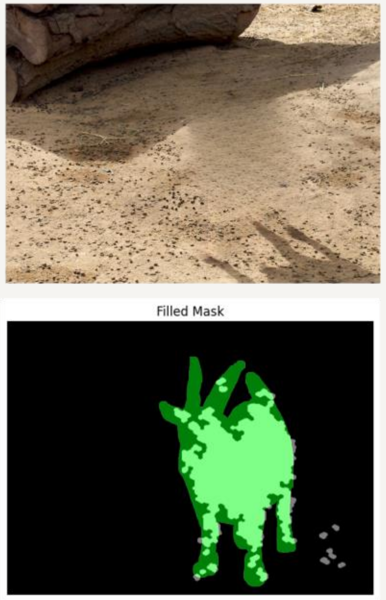
Intersection over Union



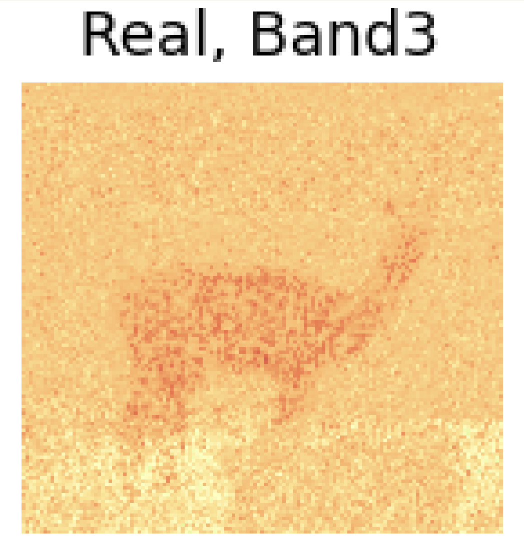
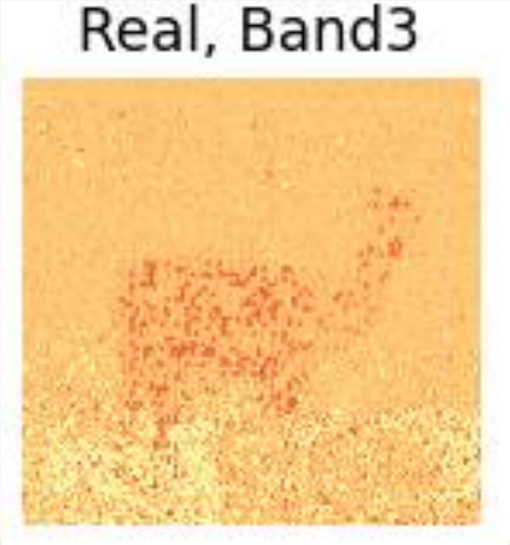
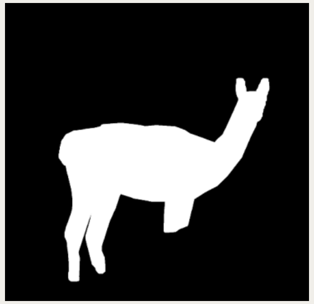
Dice Coefficient



Experiments – Image Properties

Blurred Image	Smooth Background	Natural Scenes	Patterns	Textured Background
				
Accuracy: 91.23%	Accuracy: 95.27%	Accuracy: 97.36%	Accuracy: 94.06%	Accuracy: 92.69%
IOU: 61.81%	IOU: 58.54%	IOU: 66.72%	IOU: 55.23%	IOU: 60.18%
Dice score: 76.40%	Dice score: 73.85%	Dice score: 56.42%	Dice score: 71.61%	Dice score: 75.14%

Experiments – Inpainting Methods

Original Image	MAT	LAMA	Samsung AI
			
	IOU: 0.04% Dice score: 0.88%	IOU: 65.31% Dice score: 79.02%	IOU: 31.95% Dice score: 48.43%

Concluding Thoughts

Strengths

- Achieves (reasonably) good results without deep learning.
- Adaptable to various wavelets and segmentation methods.
- Simple, lightweight implementation.

Limitations

- Relies on manual parameter tuning, which can be time-consuming and less scalable.
- Produces partial masks that highlight the inpainted region but lack object-specific accuracy.
- Fails if the inpainted region is not detectable in at least one band

Future Scope

- Test whether iterative inpainting can be detected by our pipeline.
- Design custom wavelets tailored for specific detection applications.
- Test robustness to additive noise.
- Integrate machine learning techniques for automated and optimal parameter tuning.

References and Resources

Papers and Websites:

[1] Barglazan, Adrian-Alin, and Remus Brad. “Wavelet based inpainting detection.” Advances in Artificial Intelligence and Machine Learning, vol. 04, no. 03, (2024), pp. 2783–2809

[2] Chen, Guangyong, Fengyuan Zhu, and Pheng Ann Heng. "An efficient statistical method for image noise level estimation." Proceedings of the IEEE International Conference on Computer Vision. 2015.

[3] Adrian-Alin, Barglazan, and Brad Remus. "Enhanced Wavelet Scattering Network for image inpainting detection." arXiv preprint arXiv:2409.17023 (2024).

[4] Kingsbury, Nick. "Image processing with complex wavelets." Philosophical Transactions of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences 357.1760 (1999): 2543-2560.

[5] Selesnick, Ivan W., Richard G. Baraniuk, and Nick C. Kingsbury. "The dual-tree complex wavelet transform." IEEE signal processing magazine 22.6 (2005): 123-151.

[6] http://research.google/blog/making-visible-watermarks-more-effective/

Our Code: https://github.com/GSNikhil/inpainting-detection

Thank You