BeaulieuJM.ca/publi/Bea2017a

MEAN-SHIFT POLSAR IMAGE DENOISING WITH POSITION TENSOR

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MEAN-SHIFT POLSAR IMAGE DENOISING WITH POSITION TENSOR

- MeanShift Clustering
- Distance measures for PolSAR images
- Tensor spatial attribute

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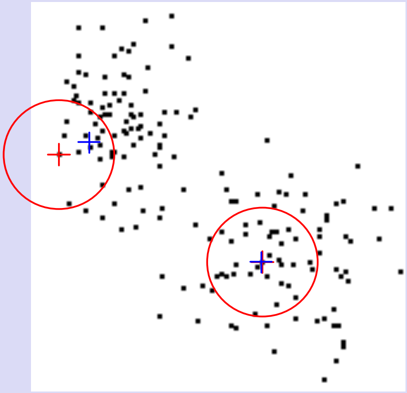
- **Mean-Shift clustering move every data points toward higher probability density zones (modes)**
- **Density → point count over a window (histogram)**
- **Direction toward higher density**

  → position of weighted mean (window)



MEAN-SHIFT

Radiometric

Distance

$D\mathit{rad} = D(Z\mathit{i},Z\mathit{j})^{1/2} \;/\; F\mathit{rad}$

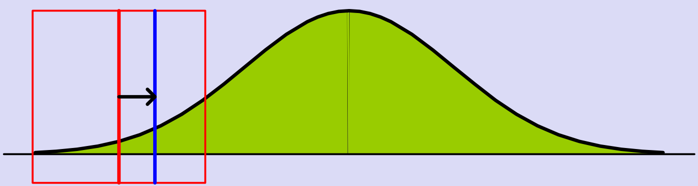
$D\mathit{spatial}$ = Distance between pixels / $F\mathit{spatial}$

$\mathrm{Weight} = \mathrm{EXP}\,[\, -\,(D\mathit{rad}^2 + D\mathit{spatial}^2)\,]$

Mean = weighted pixel mean

$\mathrm{Fhift}_R = \alpha\ \mathrm{value}_R + (1-\alpha)\ \mathrm{Mean}_R$ (radiometric value)

New Old



- **Radiometric distance D(Z*i*,Z*j*) for PolSar images**
- **Z_k is pixel covariance matrix**
- **Non textured PolSar image**
- **Z_k follows a complex Wishart distribution**

$$p(Z_k \mid \Sigma) = \frac{L^{3L} \left|Z_k\right|^{L-3} \quad \exp\left\{-L\, tr\left(\Sigma^{-1} Z_k\right)\right\}}{\pi^3\ \Gamma(L)\Gamma(L-1)\Gamma(L-2)\left|\Sigma\right|^L}$$

- **Log of the likelihood ratio statistic is**

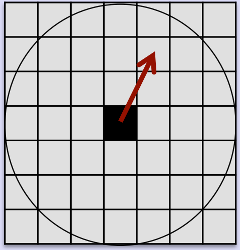
$$D(Z_i, Z_j) = 2\ln\left|\tfrac{1}{2}(Z_i + Z_j)\right| - \ln\left|Z_i\right| - \ln\left|Z_j\right|$$

- **Distance between pixels → Euclidian distance**

  Gaussian like weight (F*spatial* = σ)

  Weight = EXP [- (D*rad*^{2} +D*spatial*^{2})]

  Limited to a window (11x11)



$$\text{Shift}_R = \alpha\ \text{value}_R + (1-\alpha)\ \text{Mean}_R$$

New Old Radiometric

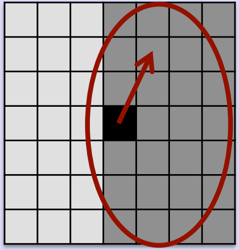
- **Shifting the pixel position**

Position

$$\text{Fhift}_p = \alpha\ \text{value}_p + (1-\alpha)\ \text{Mean}_p$$ (pixel position)

Distances between pixels will change

- **Integrating other distances (texture, shape)**
- **Using weight to define a new attribute**



$p_i = (x_i, y_i)$ → pixel position

V_i = position covariance or tensor

$$V_i = \Sigma_j \; w_{i,j} \; (p_j - p_i)\,(p_j - p_i)^t$$

i → center
j → neighbour

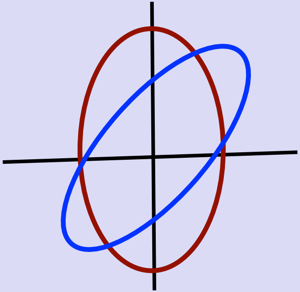
Use V_i ellipse shape (orientation, elongation)

Shape indicate <u>edge</u> orientation

- **Using V_i in weight calculation**

Use S1 measure of Garcia to calculate the difference between V_i and V_j

(BMC Evolutionary Biology 2012, 12:222)



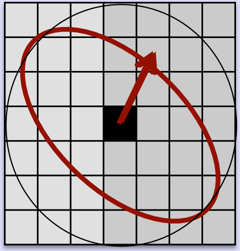
$$D_V = S1(V_i, V_j)^{1/2} \;/\; F_V$$

$$\text{Weight} = \text{EXP}[\, -(D\mathit{rad}^2 + D\mathit{spa}^2 + {D_V}^2)\,]$$

Tensor

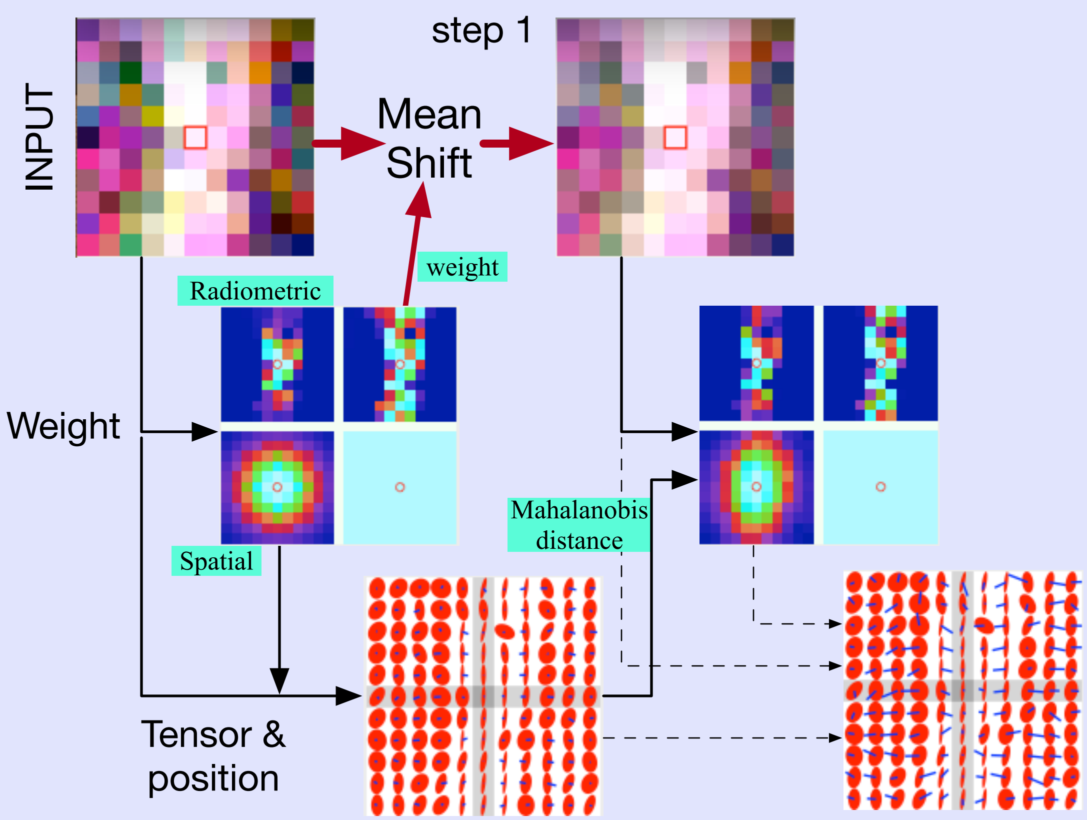
- **Shifting the value of V_i**

$$\text{Fhift}_V = \alpha\ \text{value}_V + (1-\alpha)\ \text{Mean}_V$$

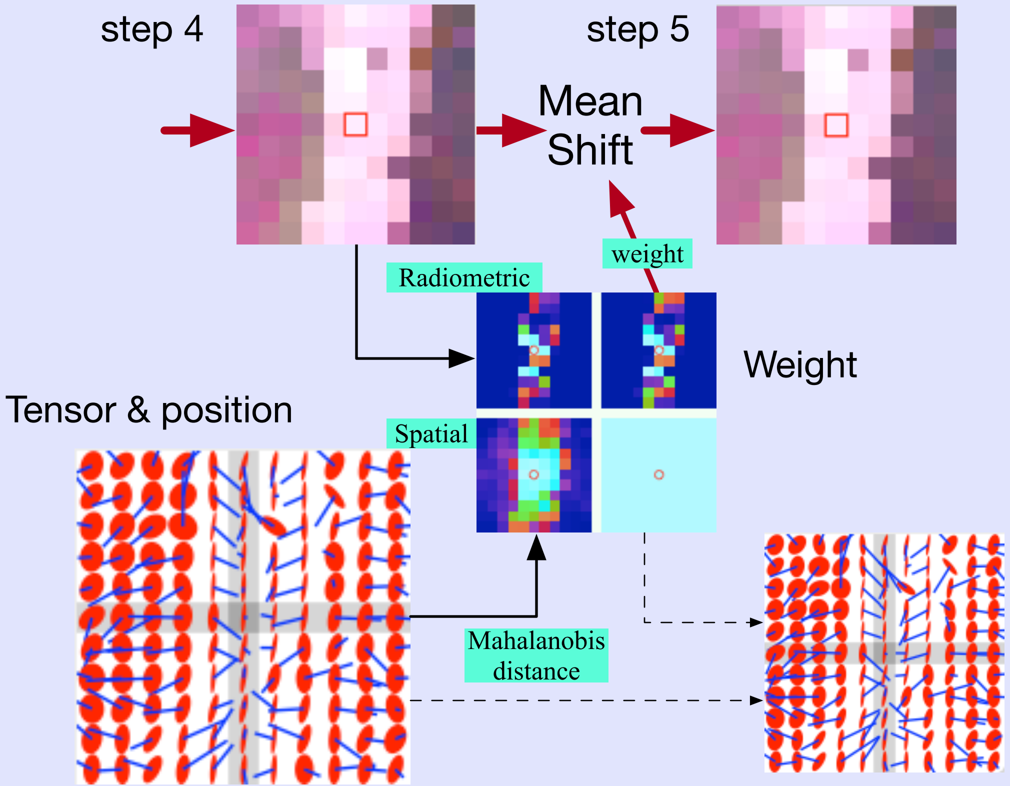


- **Mahalanobis pixel distance**

Use V_i to calculate Mahalanobis pixel distances

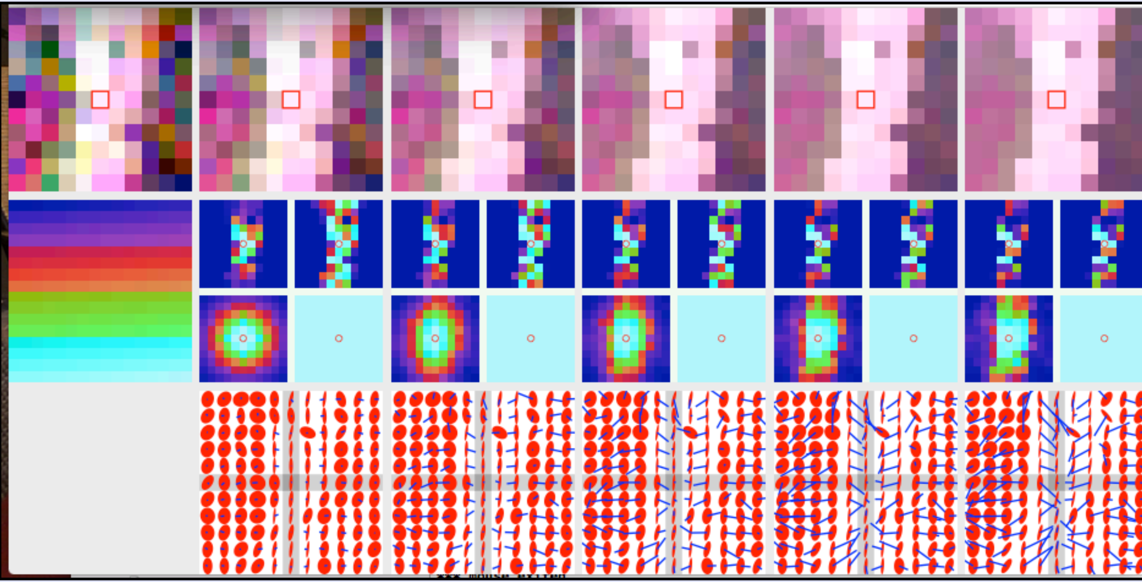


INPUT
step 1
Mean
Shift
weight
Radiometric
Weight
Spatial
Mahalanobis
distance
Tensor &
position

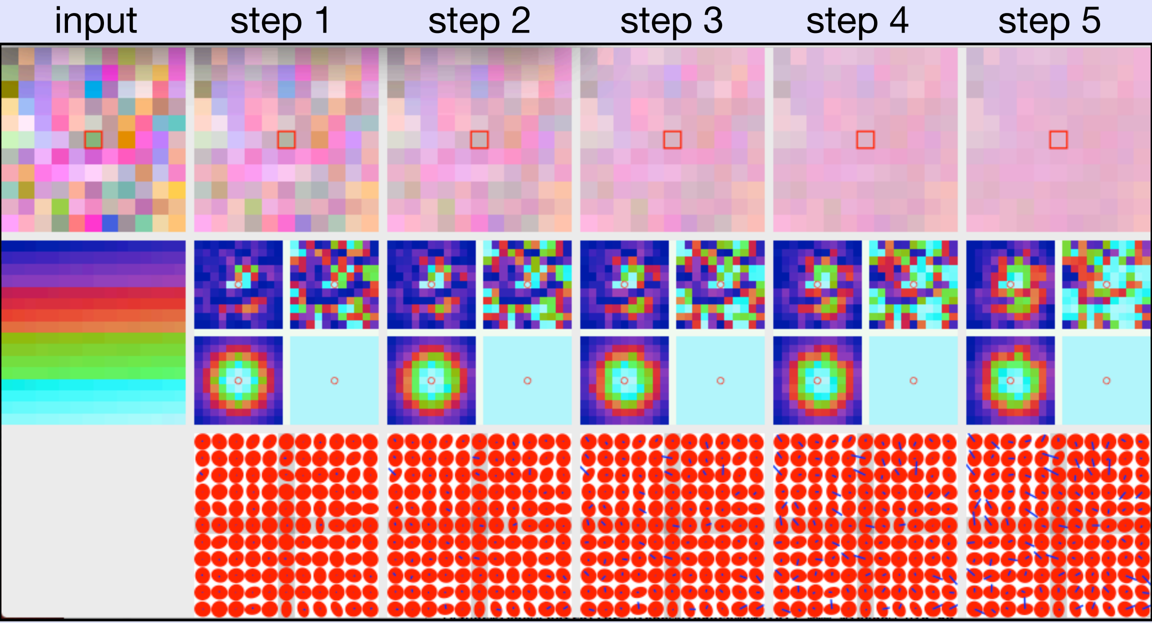

step 4
step 5
Mean Shift
weight
Radiometric
Weight
Tensor & position
Spatial
Mahalanobis distance

Vertical Structure

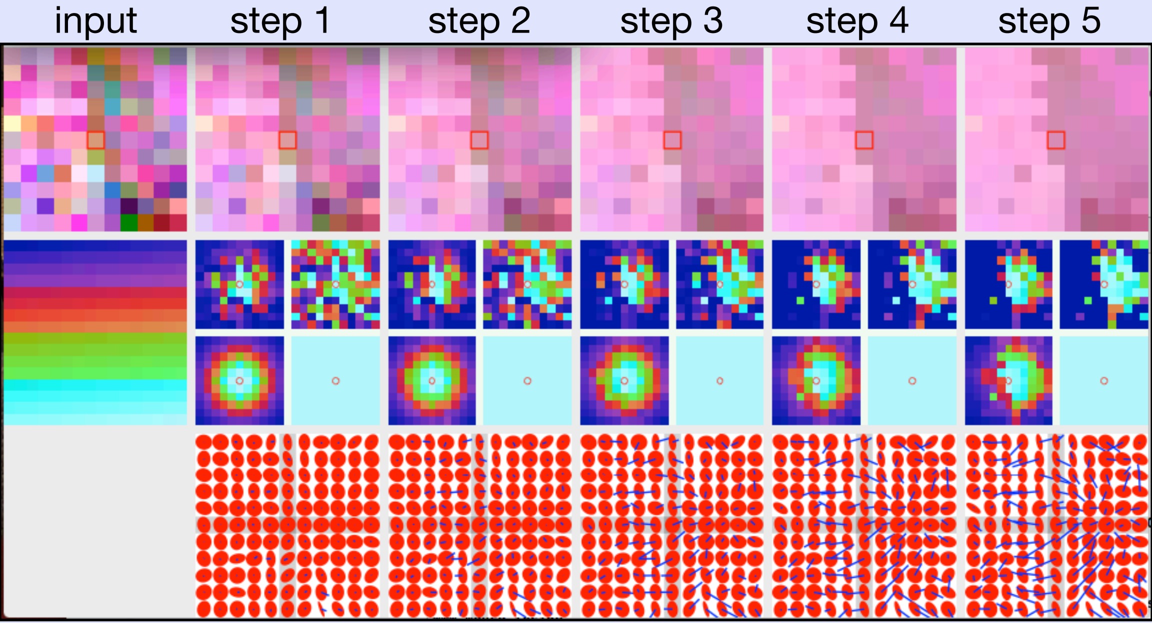
input step 1 step 2 step 3 step 4 step 5



Uniform Field

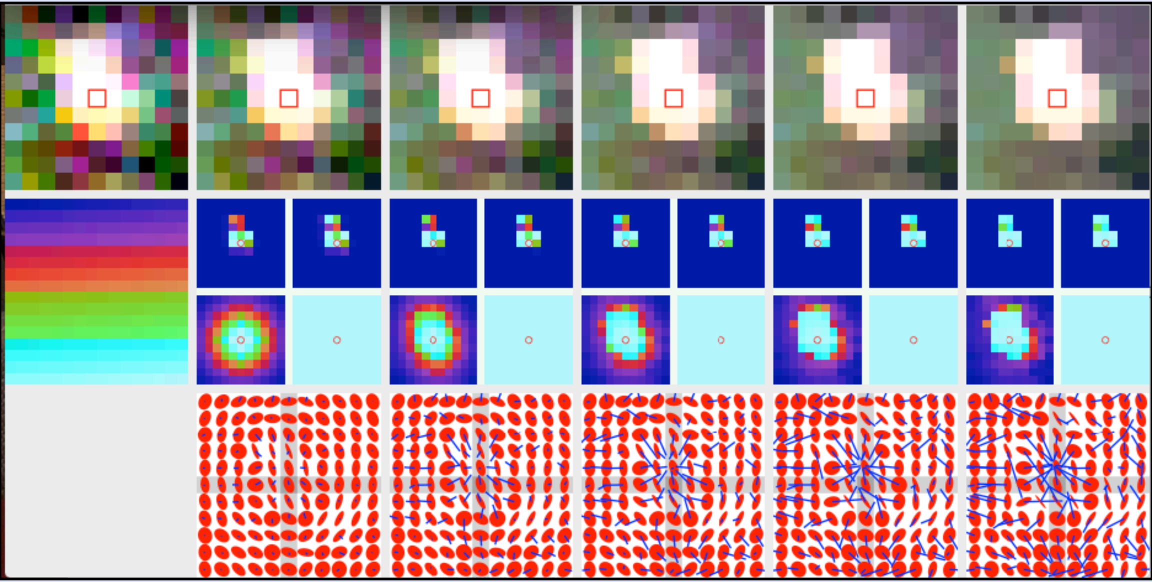


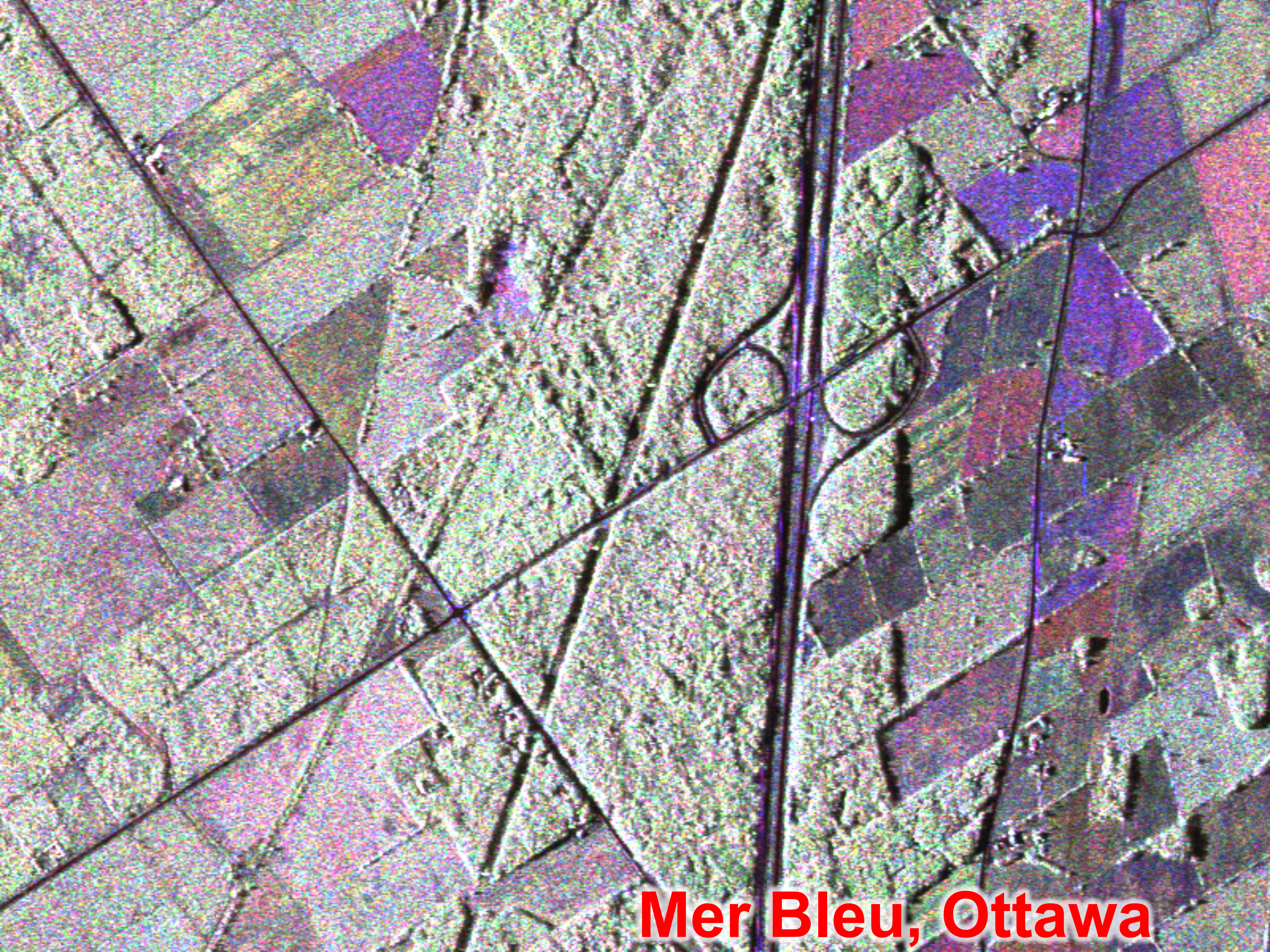
Low Contrast Edge



High Contrast Spot

input step 1 step 2 step 3 step 4 step 5

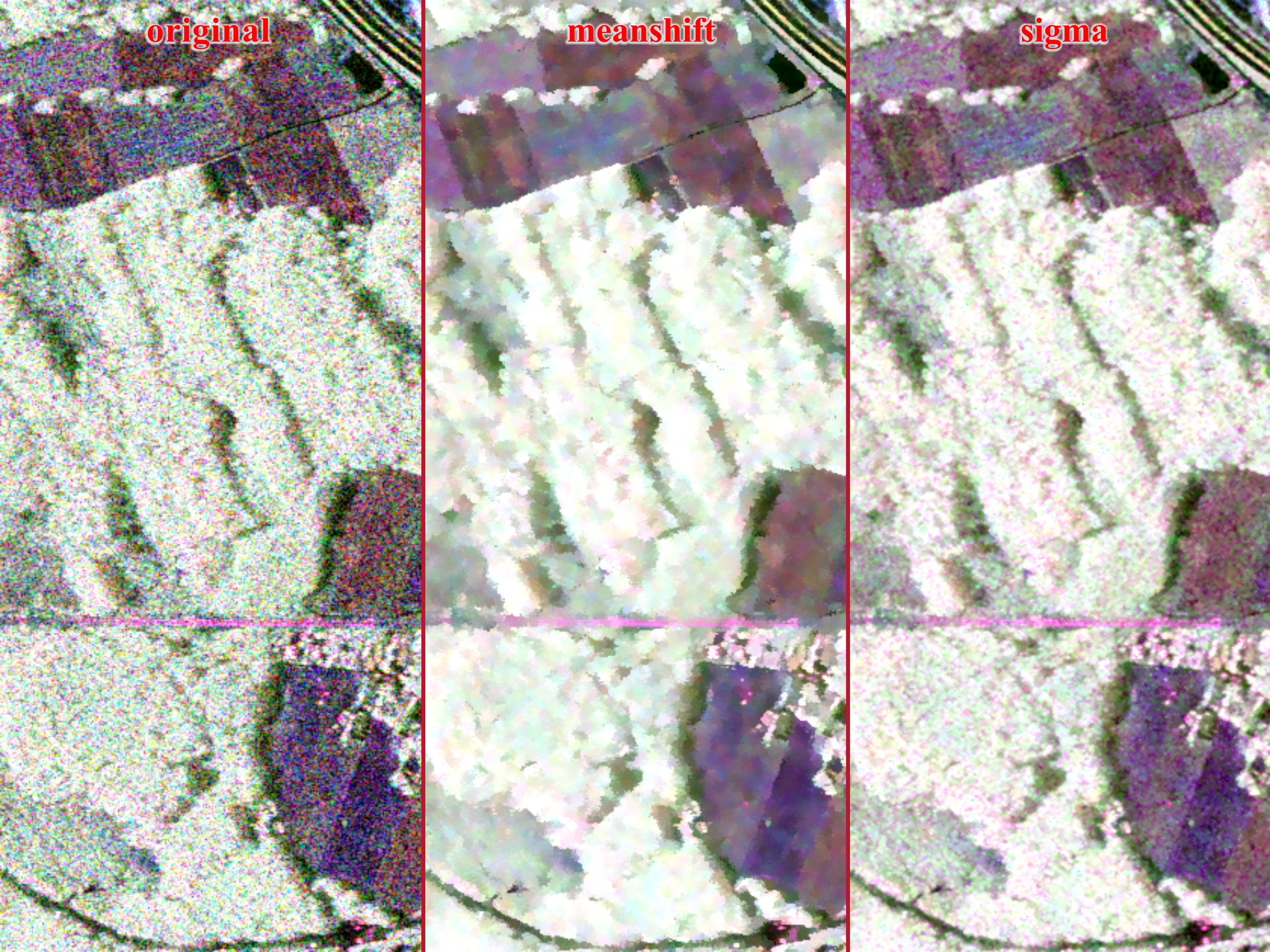



Mer Bleu, Ottawa

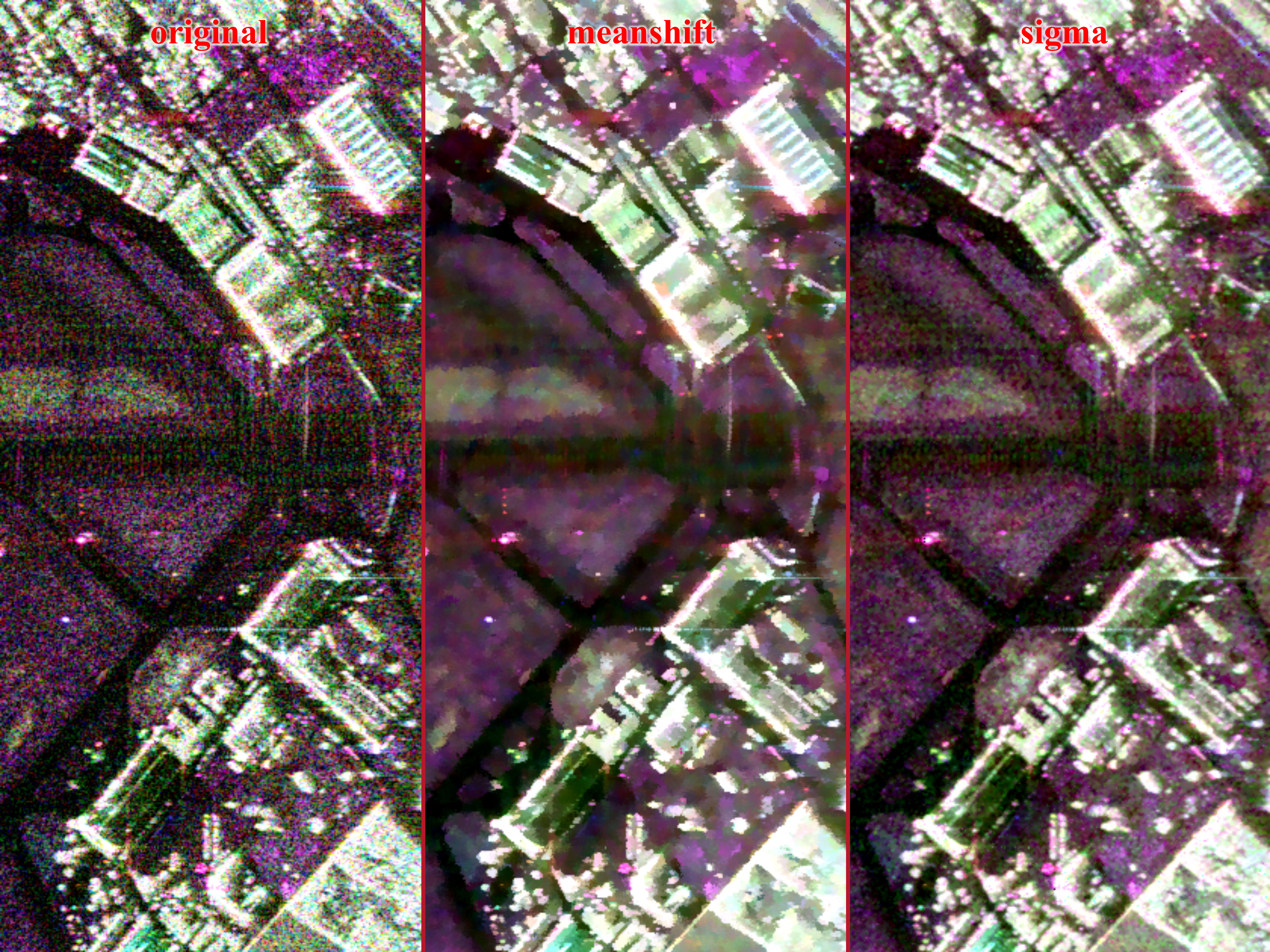

MeanShift

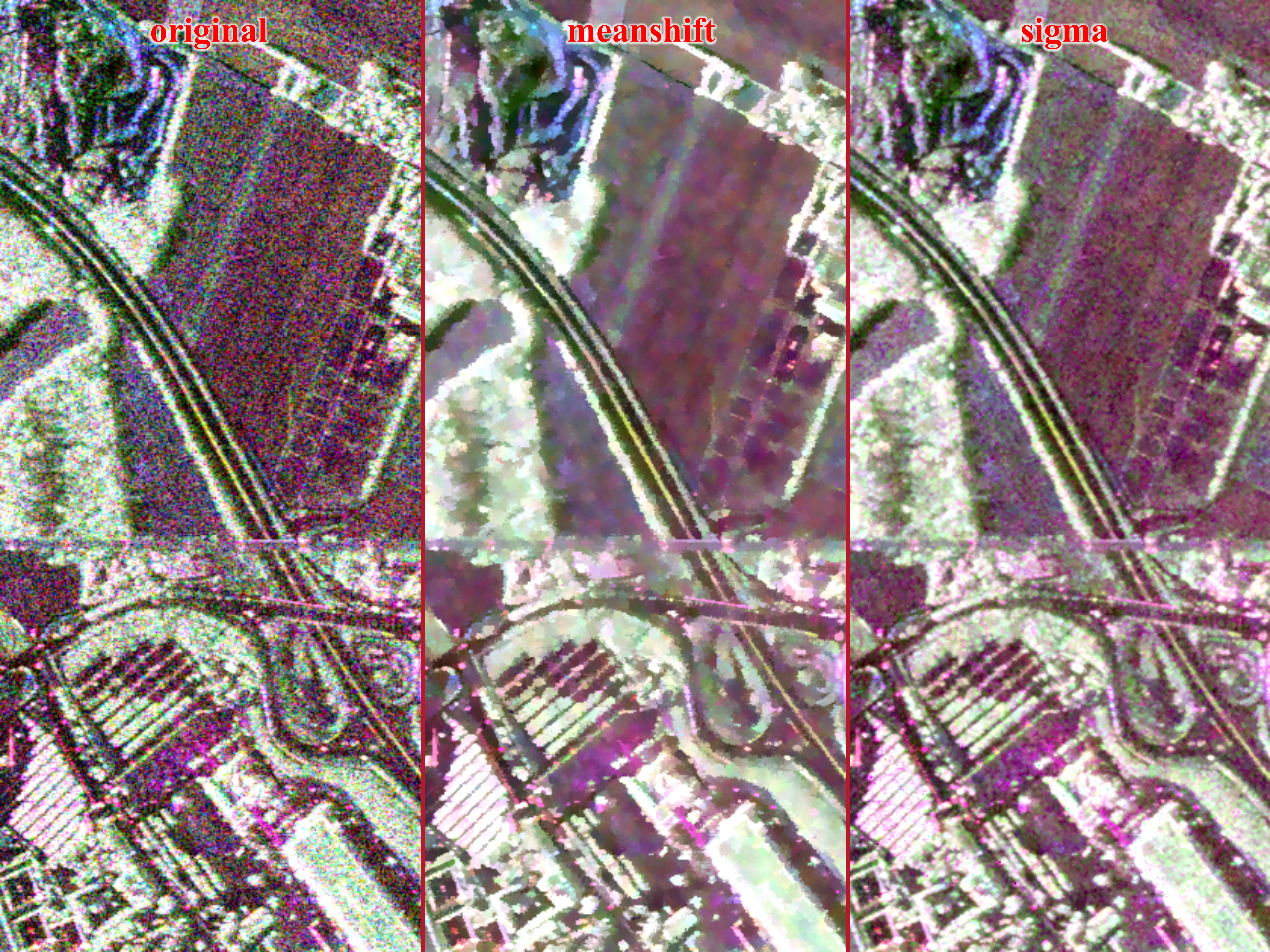
Oberfaffenhofen

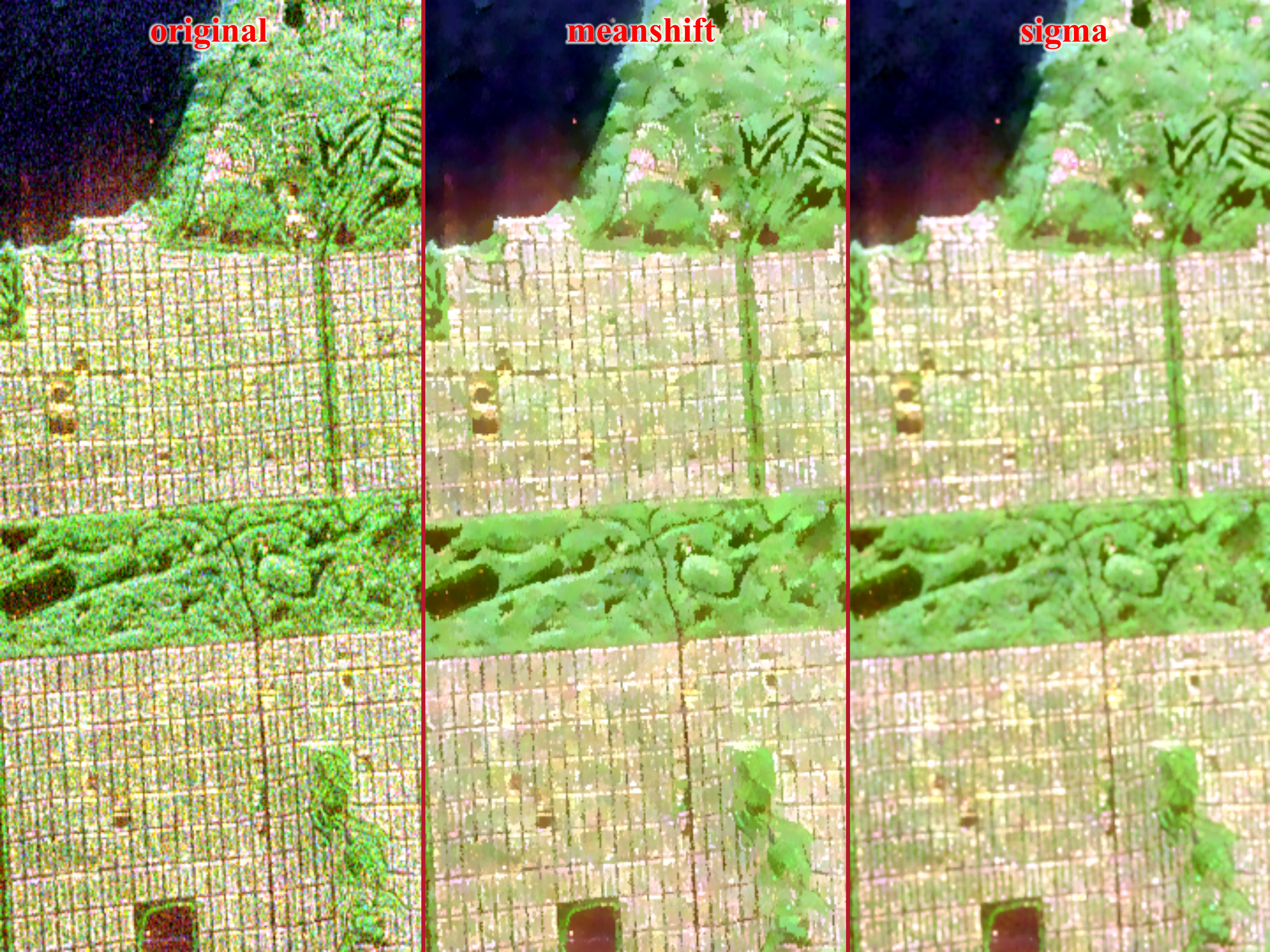
MeanShift


original
meanshift
sigma


original
meanshift
sigma


original
meanshift
sigma


original
meanshift
sigma


original
meanshift
sigma

CONCLUSION

- MeanShift can perform good image filtering.
- Position covariance tensor can provide a good textural attribute (ellipse orientation and elongation).
- Spatial attribute can be used in MeanShift to preserve edges.