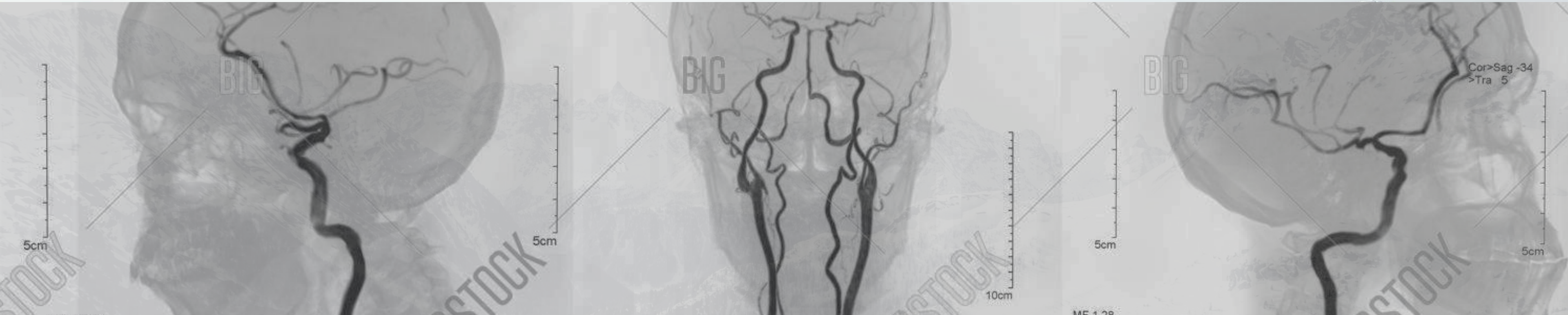
Multiscale Vessel Enhancement Filtering - Frangi’s Vesselness Measure

Fundamentals of Digital Image Processing
Githinji, P. B., Nov, 2020



A challenge with visualizing and preprocessing vessel systems is delineation of the vessel structures and suppression of the environment the vessels are in.

Frangi's Vesselness Measure: The probability that a pixel is in a vessel's region. The goal is to reduce noise and non-vascular signal while at the same time amplifying the vascular signal.

Source: Frangi et. al (1998), Mutliscale Vessel Enhancement Filtering

Workflow (1 of 2)

Hessian + Gaussian filtering

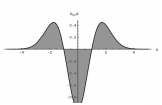
Image input (L)

Takes an image in 2D or 3D

Linear Gaussian scale-space filter

$$L(\mathbf{x}_o + \delta\mathbf{x}_o, s) \approx L(\mathbf{x}_o, s) + \delta\mathbf{x}_o^T \nabla_{o,s} + \delta\mathbf{x}_o^T \mathcal{H}_{o,s} \delta\mathbf{x}_o$$

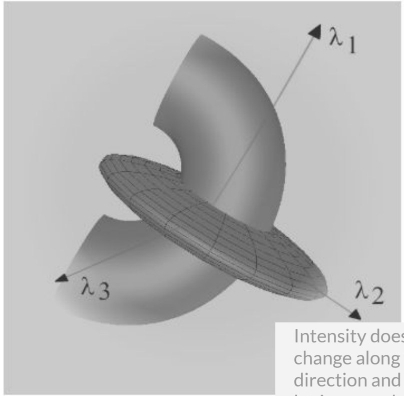
$$\frac{\partial}{\partial x} L(\mathbf{x}, s) = s^{\gamma} L(\mathbf{x}) * \frac{\partial}{\partial x} G(\mathbf{x}, s)$$



No introduction of noise as we smooth from finer scale to coarser scales

Local structure analysis at hood-level. First and Second derivatives by Taylors.Linear scale-space theory to compute the derivatives as convolution with normalized derivatives of Gaussian.

Eigenvalue decomposition - primary orientation



Intensity does not change along vessel direction and varies a lot in normal direction

Eigenvalue analysis of Hessian enables use of a single filter because the ellipsoid of the second order derivative describes the local principal direction of curvature along the vessel. Computationally more efficient.

Workflow (2 of 2)

Geometric Vesselness Measure

Traits of vessel pixels @ eigenvalues

$$|\lambda_1| \approx 0$$
$$|\lambda_1| \ll |\lambda_2|$$
$$\lambda_2 \approx \lambda_3$$

Lambda 1 signals if is in vessel because zero variation in intesity. Other eigen values measure how far from vessel center

Very small lmabda1 (ideally zero) signals that a pixel belongs to a vessel region

Geometric Ratios

$$\mathcal{R_A} = \frac{|\lambda_2|}{|\lambda_3|}.$$

$$\mathcal{R_B} = \frac{|\lambda_1|}{\sqrt{|\lambda_2 \lambda_3|}}.$$

$$\mathcal{S} = \sqrt{\lambda_1^2 + \lambda_2^2 + \lambda_3^2}$$

The smaller S is the more likely it is a background pixel. A and B are scale invariant

1st ratio: distinguishes between plate-like and line-like structures. It is zero if a line and non-zero otherwise.
2nd ratio: identifies blob-like structures only.
S: distinguishes vessel from background (noise)

Vesselness Measure & Scale

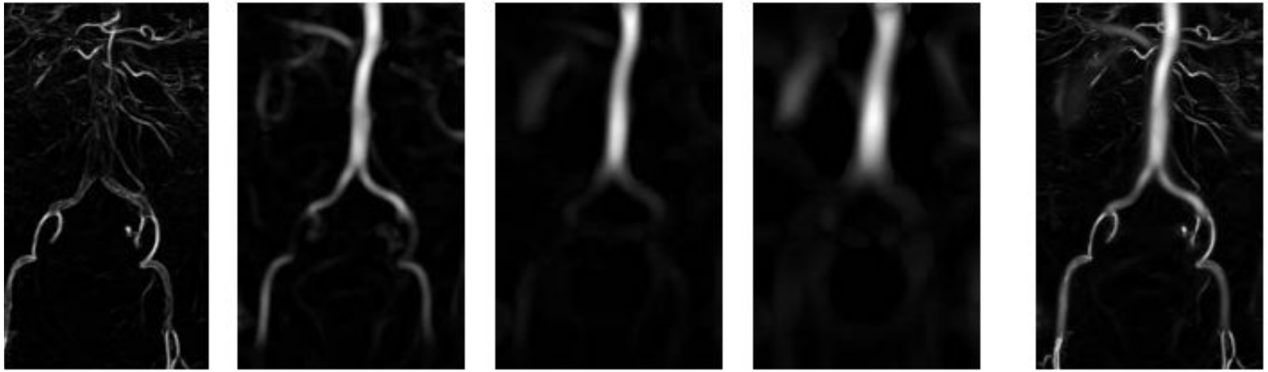
$$\mathcal{V} = \begin{cases} 0 & \text{if } \lambda_2 > 0 \text{ or } \lambda_3 > 0 \\ (1 - e^{-\frac{\mathcal{A}^2}{2\alpha^2}}) e^{-\frac{\mathcal{B}^2}{2\beta^2}} (1 - e^{-\frac{\mathcal{S}^2}{2\gamma^2}}) & \text{otherwise} \end{cases}$$

$$\mathcal{V}_o(\gamma) = \max_{s_{min} \leq s \leq s_{max}} \mathcal{V}_o(s, \gamma)$$

The result is a probability measure.

Three parameters for three criteria:
V is a product of the three to ensure is maxima
only if all three are fulfilled.
Scale:

How scale works

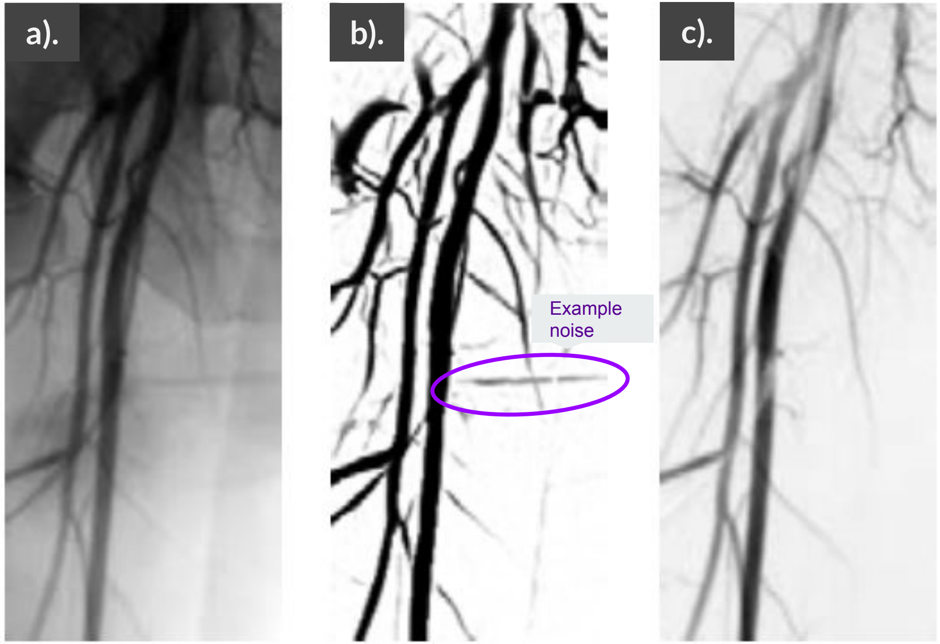


4. The first four images show the vesselness obtained at increasing scales. The last image is the
lt after the scale selection procedure.

A vesselness measure at different scale values is determined resulting in a separate image for each scale, where each image shows vessels of different widths. The final output uses the maximum of the vesselness over the range of scales used.

Source: Frangi et. al (1998), Mutliscale Vessel Enhancement Filtering

Results: Frangi suppresses background and improves contrast of vessels



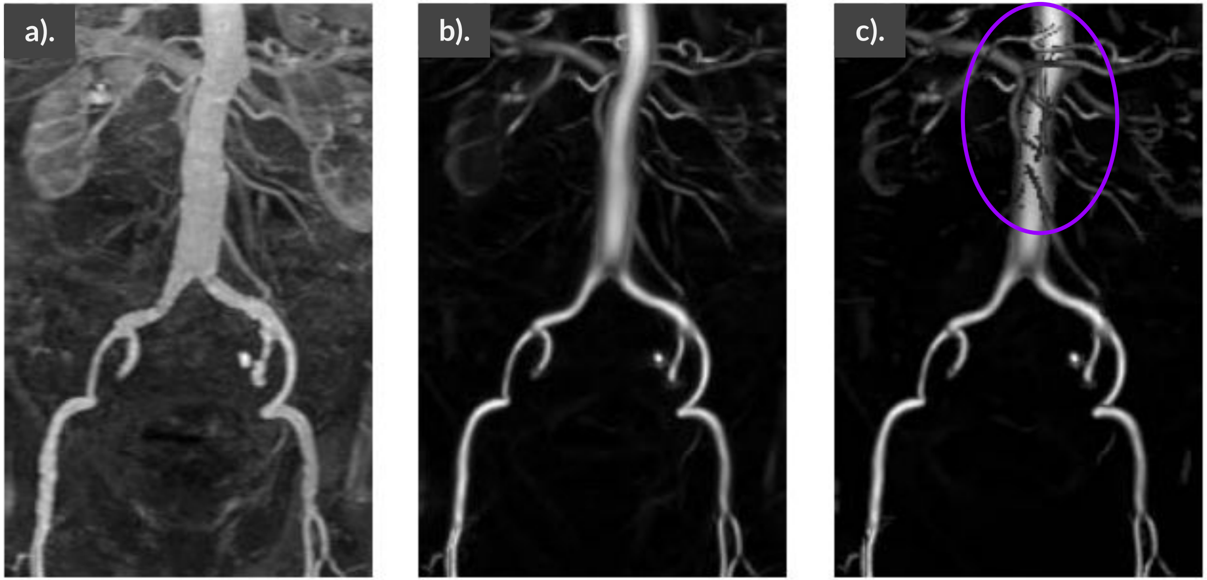
a). Is the original image taken by the equipment when a contrasting agent has been injected.

b). Output of Frangi's vesselness filter on the original image.

c). Comparison image obtained by subtracting the original image with a reference image where a contrasting agent has not been used.

Source: Frangi et. al (1998), Mutliscale Vessel Enhancement Filtering

Results: Superior enhancement for quality results in subsequent steps/applications



a). Is the original maximum intensity projection image

b). Vessel enhanced image greatly suppresses background

c). Closest vessel projection, which reveals depth in 3D image

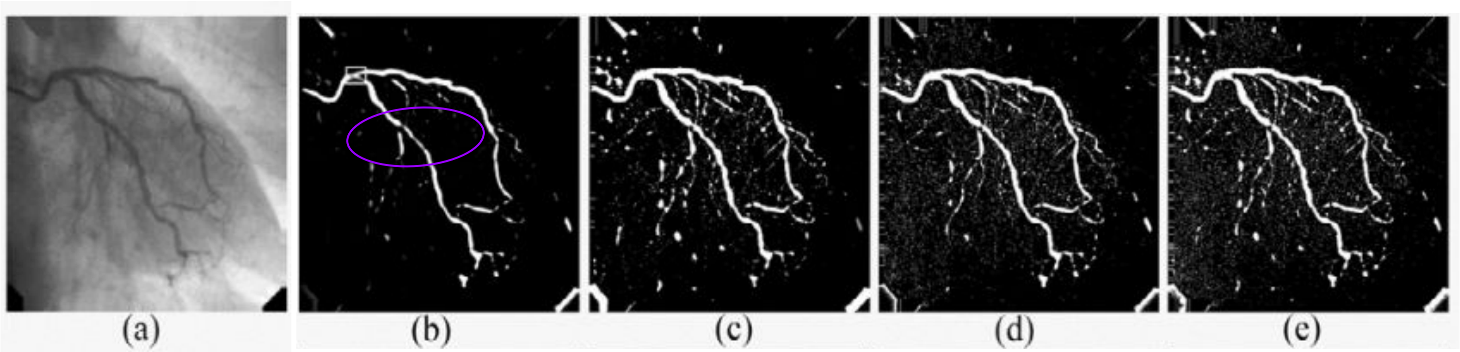
Source: Frangi et. al (1998), Mutliscale Vessel Enhancement Filtering

Other Related Approaches

- Vesselness measure
- Morphology

TODO: distinct xtics

Frangi Vs Other Vesselness Measures



Input image

Frangi et. al

1998

Ying et. al

2015
Transformation function with a contrast enhancement parameter

Yanli et. al

2012
Thresholding of lambda-2, morphological consideration

Wang et. al

2012

Frangi has superior background and noise reduction. However, it has disconnections at junctions

Source: Frangi et. al (2016), Performance Comparison of Vesselness Measures for Segmentation of Coronary Arteries in 2D Angiograms

Frangi Vs Morphological Processing

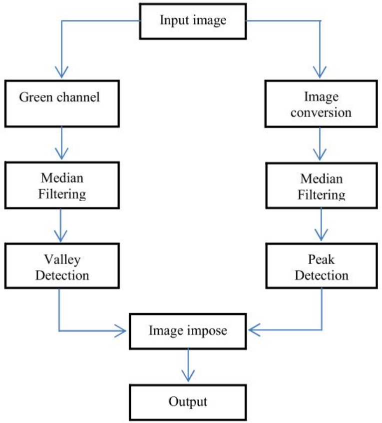
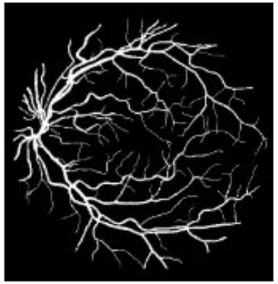


Fig.1. Flow chart blood vessel extraction



Ground truth vessel extraction from Drive Database

Fig.9. Proposed method

Information on small veins is lost

Source: Mustafa et. al (2014), Blood vessel extraction using morphological operation for Diabetic Retinopathy

Frangi Filter

Continues to be state of the art

Sato

Basis for Frangi's Filter

Uses information in the eigenvalues of the second order derivative Hessian matrix
BUT does not use all the eigen values e.g. just two of the three in 3-D case.

Frangi

Great suppression and delineation

Builds on Sato's approach and makes use of all the eigen values.
Great at delineation and suppression but challenged by bifurcations

Post Frangi

Improve efficiency and continuity of branches

Frangi continues to be state of the art and improvements are made to enhance it.
Even FrangiNET, a CNN representation, does just as well as Frangi filter .

Code Examples:

Compare Frangi to

- Similar Hessian-based filters
- Edge detectors
- Morphological operators

Code: https://bit.ly/2KbmuPz

Methods using similar approaches

Hessian matrix

Describes local curvature of a function. Eigenvalues analysis

- Frangi
- Meijering - neurites
- Sato

Edge detectors

Where contrast changes sharply. Derivatives and gradient direction

- Canny
- Laplacian of Gaussian
- Sobel
- Scharr

Structural info

Analysis of geometrical structures - form and structure of image

- Morphological processing - erode, dilate, open, close
- Choice of structuring element

General workflow

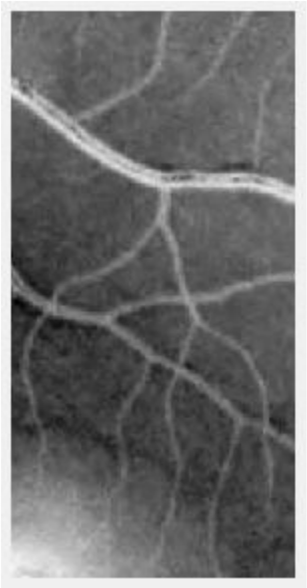
Input
Prepare image format for analysis
Input image as grayscale and float

Smooth
Suppress noise. Except for ridge operators
Gaussian filter as standard

Apply Filter
Apply the different filters accordingly using the same smoothed image and similar parameters where possible

Mashup
Where feasible or opportunistic combine outputs of different filters using product

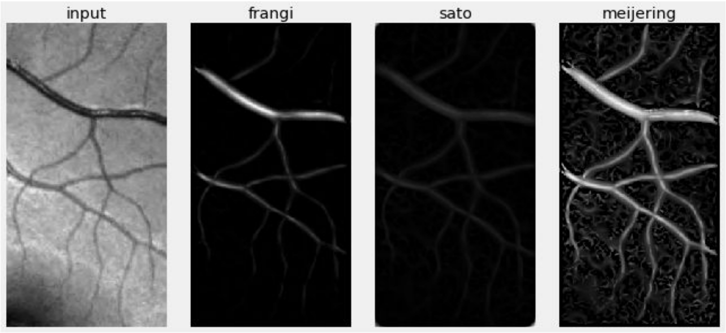
Compare
Visual output and comparison of results.



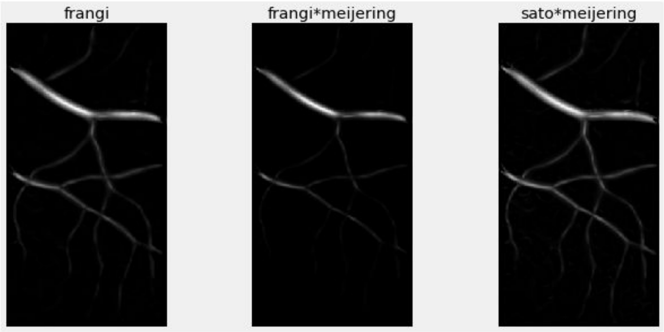
Testing Image Source: skimage package

Frangi Vs Hessian-based Ridge Operators

1. No mashup



2. Yes mashup



Frangi has strongest background suppression.

Meijering has strongest vessel signal/contrast enhancement but has noisy edges and background

A product of sato and Meijering seems to do somewhat better than Frangi by itself - smaller vessels have more contrast

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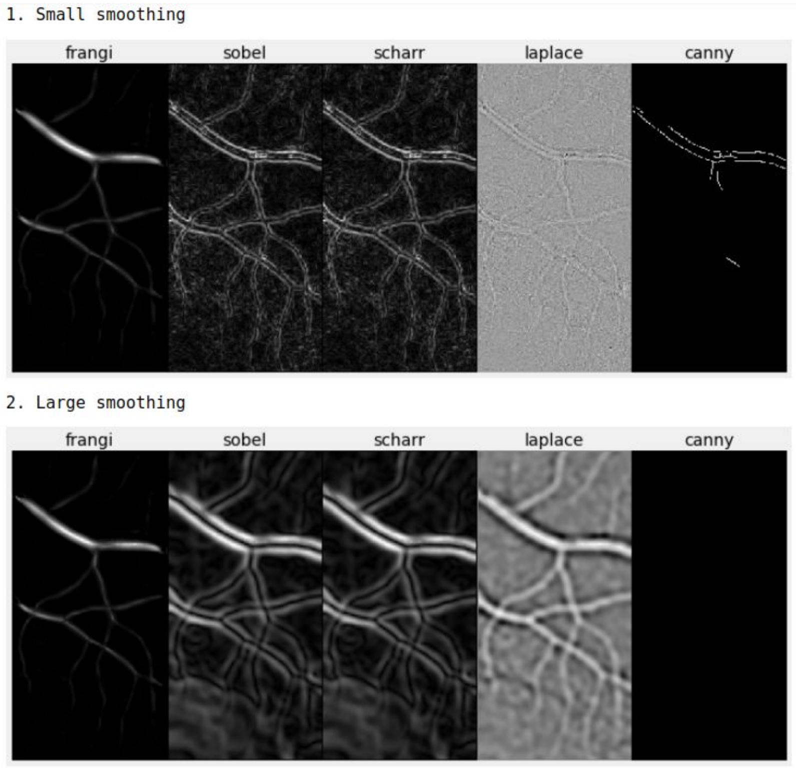
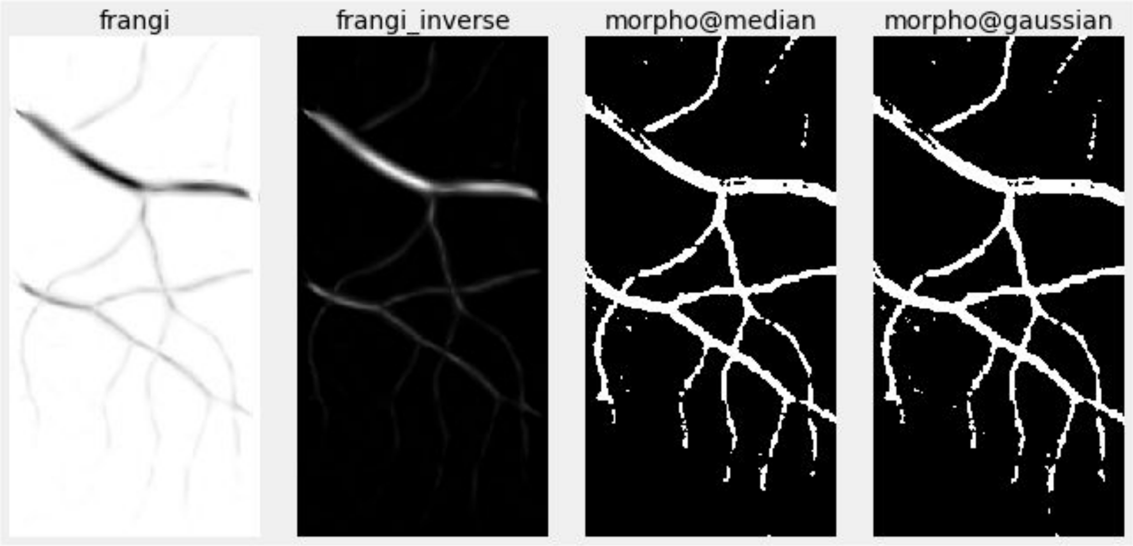
==== Product operation Mashup ====
MSE: (meijering - frangi)      0.0343
MSE: (meijering - sato)        0.0325
```

Frangi Vs Edge Detectors



Edge detectors do not differentiate between background and foreground (vessel) edges.

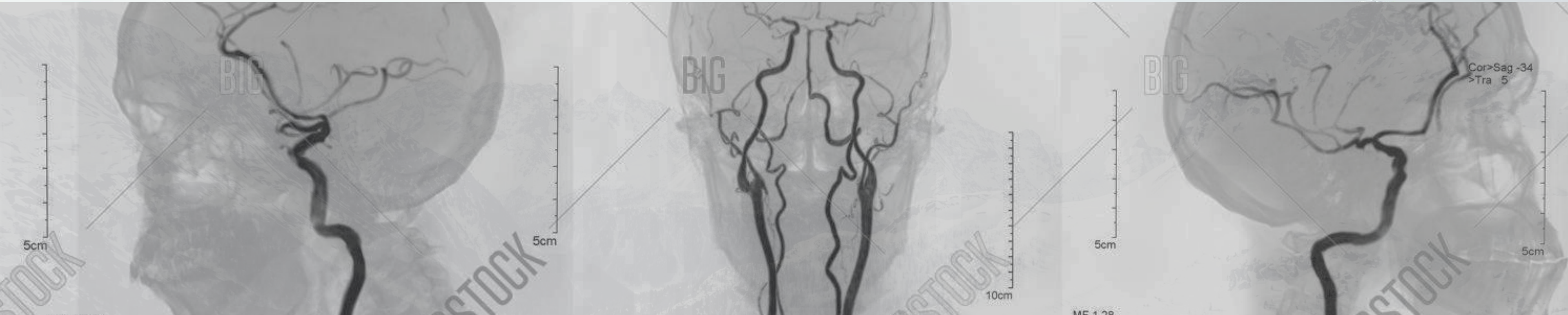
Frangi Vs Morphological cont



More Exploration??

- Phase Congruency filtering
- FrangiNET implementation
-

Thank you.



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Scikit Ridge Operators, https://scikit-image.org/docs/dev/auto_examples/edges/plot_ridge_filter.html

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