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Edge Detection, Contouring, and Transmission Measurement (partial)

Assuming elliptical symmetry, we define a distance metric

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Sampling multiple points, we then obtain a system of linear equations in a_n

$$B_i = \sum_n a_n s_i^{2n}$$

Rewrite the previous as matrix equation

$$B = SA$$

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$$s_i^2 = (i+1) \cdot s^2$$

Performing row reduction on S, we obtain a nice pattern:

$$[S'|I] = \begin{bmatrix} 1 & 1 & 1 & 1 & \cdots & 1 & 0 & 0 & 0 & \cdots \\ 1 & 2 & 4 & 8 & \cdots & 0 & 1 & 0 & 0 & \cdots \\ 1 & 3 & 9 & 27 & \cdots & 0 & 0 & 1 & 0 & \cdots \\ 1 & 4 & 16 & 64 & \cdots & 0 & 0 & 0 & 1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

$$[T|C] = \begin{bmatrix} 1 & 1 & 1 & 1 & \cdots & 1 & 0 & 0 & 0 & \cdots \\ 0 & 1 & 3 & 7 & \cdots & -1 & 1 & 0 & 0 & \cdots \\ 0 & 0 & 2 & 12 & \cdots & 1 & -2 & 1 & 0 & \cdots \\ 0 & 0 & 0 & 6 & \cdots & -1 & 3 & -3 & 1 & \cdots \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

This pattern was calculated and verified to hold until at least n = 10

Thus, we can obtain A by instead solving the equation

$$CB = CSA$$

using back substitution.

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Once A is determined, the baseline approximation can be computed recursively as

$$f_0 = a_N$$

$$f_n = s^2 f_{n-1} + a_{N-n}$$

$$B_N(s) = f_N$$

This baseline is then subtracted from the total image.

Flattening Results

To reduce noise, first a gaussian blur was used to "average out" the initial image, before the process of flattening.

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The morphological transforms were determined by trial and error, adjusting the order of transformation and size of the kernel.

Denoising Results

Edge detection is can be done using a gradient method, such as Sobel Derivatives and the Laplacian, to detect where the intensity of an image changes quickly—an "edge"

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While I have proposed these methods, I haven't been able to test them too much.

Flake Determination Results

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Alternative colour spaces may be better suited for analysis than the default BGR colourspace.

Code

https://github.com/daedalus1235/FlakeAutoFind.git (private repo) Written in C++ using OpenCV, compiled with CMake and g++.