# <span id="page-0-0"></span>SPEXone L1A-L1B processor updates: stray light and binning

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- ▶ The stray light model was based on analytical diffuse and ghost kernels.
- ▶ The kernels were determined from fits to (simulated) stray light calibration measurements.



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▶ However, real calibration measurements have too much structure for an analytical formalism.



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- ▶ Construct a stray light kernel from measurements of multiple exposure times and across track (ACT) angles. This increases the signal to noise (SNR) ratio.
- ▶ Normalize and set values within a radius of the image center to 0



However, the kernel looks different at different parts of the detector.

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- ▶ Divide the detector into regions and derive a stray light kernel corresponding to each region.
- Each kernel  $K_k$  has associated weights  $w_k$  which define its region of influence or domain.



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In order to activate a kernel k only within in its domain (box) we define a weight for it:

$$
w_{k,ij} = w_{k,i} w_{k,j},
$$
  
\n
$$
w_{k,i} = \begin{cases} \frac{i-i^{\downarrow}}{i_0 - i^{\downarrow}} & i^{\downarrow} \leq i < i_0\\ \frac{i^{\uparrow} - i}{i^{\uparrow} - i_0} & i_0 \leq i < i^{\uparrow},\\ w_{k,j} = \begin{cases} \frac{j-j^{\leftarrow}}{j_0 - j^{\leftarrow}} & j^{\leftarrow} \leq j < j_0\\ \frac{j^{\rightarrow} - j}{j^{\rightarrow} - j_0} & j_0 \leq j < j^{\rightarrow}. \end{cases} \end{cases}
$$
\n(1)

► Outside the box 
$$
(i^{\downarrow}, i^{\uparrow}, j^{\leftarrow}, j^{\rightarrow})
$$
 the **kernel should have no effect.**

 $\blacktriangleright$  The box boundary is at the center of a neighboring kernel or a detector edge.



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 $\triangleright$  Convolution with multiple kernels:

$$
S_{ij}^{\text{conv}} = \sum_{k} \sum_{m=0, n=0}^{m=N, n=N} w_{k, mn} K_{k, ij, mn} S_{mn}^{\text{ideal}}, \qquad (2)
$$

where  $\boldsymbol{S}^\text{ideal}$  is an ideal signal,  $\boldsymbol{K}_k$  is the  $k$ th kernel,  $\boldsymbol{w}_k$  the corresponding weight,  $\boldsymbol{S}^\mathsf{conv}$  the convolved signal, and  $N$  is the detector dimension.



$$
w_{k,mn} \to w_{k,mn}/\sum_{k} w_{k,mn}, \tag{3}
$$

so that at each pixel the kernel weights add up to 1.

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## ▶ The standard Van Cittert deconvolution algorithm is

$$
S_{ij}^{(v+1)} = \frac{S_{ij}^{(0)} - \sum_{mn} K_{ij,mn} S_{mn}^{(v)}}{1 - \sum_{mn} K_{ij,mn}},
$$
(4)

where  $\boldsymbol{S}^{(0)}$  is the convolved image,  $\boldsymbol{K}$  is a kernel, and  $\boldsymbol{S}^{(v+1)}$ is the updated image after  $(v + 1)$ th iteration.

 $\blacktriangleright$  The sum in the denominator is called the internal scattering factor:

$$
\eta_{ij} \equiv \sum_{mn} K_{ij,mn}.\tag{5}
$$

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 $\triangleright$  With multiple kernels the Van Citter algorithm is

$$
S_{ij}^{(v+1)} = \frac{S_{ij}^{(0)} - \sum_{k} \sum_{mn} w_{k,mn} K_{k,ij,mn} S_{mn}^{(v)}}{1 - \sum_{k} \eta_{k,ij}}.
$$
 (6)

 $\triangleright$  The weights can be absorbed into the signal and thus there are no difficulties computing the convolutions:

$$
\tilde{S}_{k,mn}^{(v)} = w_{k,mn} S_{mn}^{(v)},
$$
\n
$$
\sum_{k} \sum_{mn} w_{k,mn} K_{k,ij,mn} S_{mn}^{(v)}
$$
\n
$$
= \sum_{k} \sum_{mn} K_{k,ij,mn} \tilde{S}_{k,mn}^{(v)}
$$
\n
$$
= \sum_{k} \mathbf{K}_{k} \otimes \tilde{\mathbf{S}}_{k}^{(v)}.
$$
\n(7)

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- ▶ In principle, each convolution  $K_k \otimes \tilde{S}_k$  operates on all pixels of the detector.
- If the kernel has "extent" r meaning that  $K_k$  is 0 at r pixels from its center - we only need to consider a subimage  $\tilde{S}_k^s$  with a box side of  $W + 2r$  and a kernel with box side of  $W + 6r$ where W is the length of a box side defined by the weight  $w_k$ .
- ▶ We test two different kernel extents:
	- $\blacktriangleright$   $r = 512$  pixels
	- $\blacktriangleright$   $r = 256$  pixels
- $\triangleright$  We also test using a smaller number of kernels by skipping some wavelengths — from 50 to 30 kernels.
- <span id="page-10-0"></span> $\blacktriangleright$  In this delivery, the L1A product has been generated using the real flight binning table.
- ▶ This significantly speeds up noise progapation during the demodulation step in the L1A-L1B processor.

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- $\blacktriangleright$  The new delivery is located at [https://public.spider.surfsara.nl/project/](https://public.spider.surfsara.nl/project/spexone/PACE/L1A-L1C/2022_10_06/) [spexone/PACE/L1A-L1C/2022\\_10\\_06/](https://public.spider.surfsara.nl/project/spexone/PACE/L1A-L1C/2022_10_06/)
- $\triangleright$  release\_notes.pdf explains the content of the delivery, including how to build and run the software.
- $\blacktriangleright$  The objective is to have three successful runs:

# 50 kernels, kernel extent r = 512 pixels mpirun -np <n> <spexone> L1B\_full.yaml # 30 kernels, kernel extent r = 512 pixels mpirun -np <N> <spexone> L1B\_30\_kernels.yaml # 50 kernels, kernel extent r = 256 pixels mpirun -np <N> <spexone> L1B\_reduced.yaml

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Using an AMD Ryzen 9 5950X, 10 cores, 5000 images in L1A product:



(Using a better value of [l1b][first\_proc\_rel\_workload] could save 5–10 min)

Processor output using L1B\_reduced.yaml:



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