# Separating image structures via graph-based seeded region growing

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### Data description

- X-ray observatory data: spatial coordinates and energy of photons detected.
- Binning the data gives us an X-ray image.

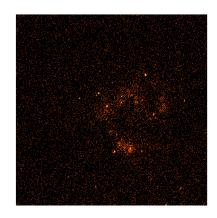


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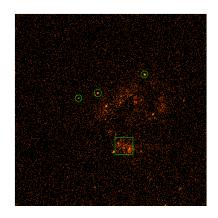


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- Binning the data gives us an X-ray image.
- Shows point sources and extended sources.
- Our task: separate the structure of sources from the background.

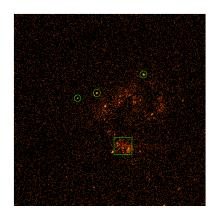


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#### Inhomogeneous Poisson process

- Assumption: the detected photons follow an inhomogeneous Poisson process with density  $\lambda(y)$ .
- For any set A,  $N(A) \sim \mathsf{Pois}\left(\int_A \lambda(y) dy\right)$ .
- N(A): the number of photons contained in set A.

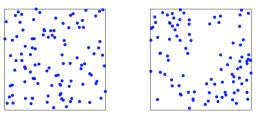
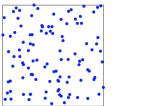


Figure: A homogeneous Poisson process (left) and an inhomogeneous Poisson process (right). (Credit: Mahling et al.)

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- We denote these photons as  $\{p_1, p_2, \cdots, p_n\}$  as an realization of the Poisson process.



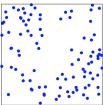


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#### Voronoi tessellation

- Imagine that there are n points on the plane.
- Divides the plane into n cells  $\{C_1, C_2, \cdots, C_n\}$  such that cell  $C_i$  contains all locations closer to point  $p_i$  than to any other point.

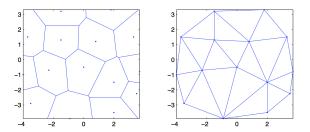


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- Delaunay triangulation: the dual graph of Voronoi tessellation.

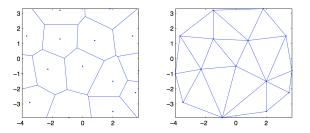


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#### Voronoi estimator

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- $\mu(\cdot)$  is the Lebesgue measure on  $\mathcal{R}^2$  (i.e., area).



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- Construct the following graph:

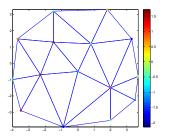
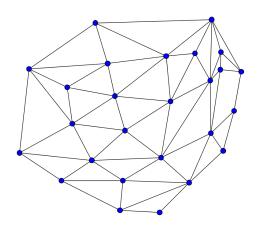


Figure: The graph constructed (each node has a value).

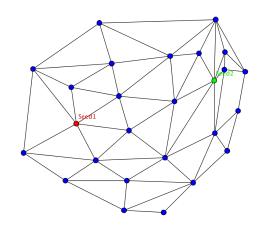
# Graph-based seeded region growing (G-SRG)

- The SRG was first proposed by Adams et al. (1994).
- It is an algorithm used for image segmentation: separates an image into several regions such that each region is composed by connected pixels with similar values.
- We extend the usage of it from images to graphs.

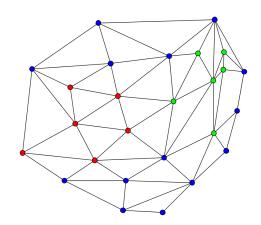
 Imagine that there is a graph, and each node of it has been assigned a value.



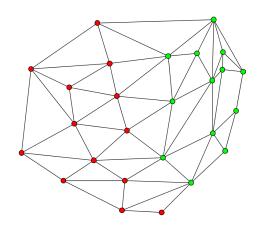
 Place a set of seeds in the graph, where each seed can be a single node or a set of connected nodes.



 Grows these seeds into regions by successively adding neighboring nodes.



 Finishes when all nodes in the graph are assigned to one (and only one) region.



## The growing strategy

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- In detail, it chooses the pair of a growing region and its neighboring node such that the following criterion is minimized:

$$\delta(x,R) = \left| g(x) - \frac{\sum_{i} A(r_i)g(r_i)}{\sum_{i} A(r_i)} \right|.$$

•  $g(\cdot)$ : a function mapping a node index to its value.  $r_i$ : the *i*-th element of region R.  $A(r_i)$ : the area of the Voronoi cell containing  $r_i$ .



## How to specify the seeds?

- The seeds of sources:
  - Use the algorithm called Mexican-Hat Wavelet source detection (wavdetect), which is implemented in CIAO 4.6.
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  - We specify nearby nodes as the seeds of sources.
- The background seeds: they can be just specified manually.



#### Example one: two point sources

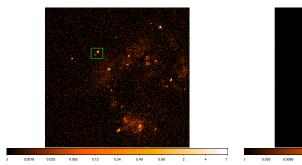


Figure : Region of interest (within the rectangle).

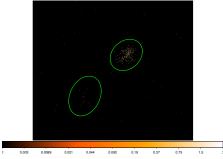
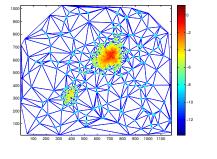


Figure : Region of interest after zooming in.

### Example one: two point sources (cont.)



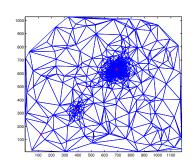


Figure: Graph constructed by Delaunay triangulation (after log transformation).

Figure : Seeds specified by wavdetect (three red dots).

#### Example one: two point sources (cont.)

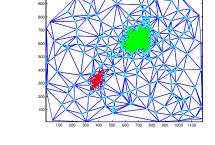


Figure : Result of G-SRG (clustering of photons)

Figure : Result of G-SRG (clustering of Voronoi cells)

# Example two: two embedded point sources in a field of structured extended emission

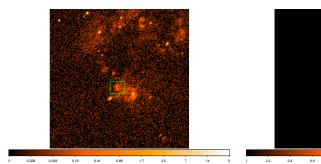


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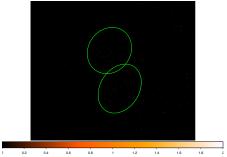
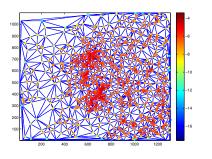


Figure : Region of interest after zooming in.

# Example two: two embedded point sources in a field of structured extended emission (cont.)



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Figure: Graph constructed by Delaunay triangulation (after log transformation).

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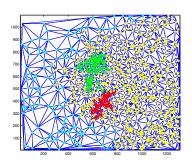


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#### Pros and Cons

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- Robustness: the result is not affected by the parameters, e.g., the bin size and the location of the background seeds.
- Fast computation: the computational speed depends on the number of photons. The time complexity of Voronoi tessellation is  $O(n\log n)$ . The time complexity of G-SRG is at most  $O(n^2)$ . (On macbook, 10 seconds for n=1500.)

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#### Cons:

- G-SRG is an ad-hoc method, which lacks a theoretical support.
- It requires the specification of the seeds of sources, which affects the outcome of G-SRG significantly.

#### References I



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