Applications of Machine Learning and Computer Vision in Analysis of Timepix3 Data

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On the menu today

Several *selected* nice examples … by no means exhaustive!

Topics:

- Trajectory estimation & reconstruction (CV),
- Particle identification (ML),

If interested, watch for references in the bottom of slides.

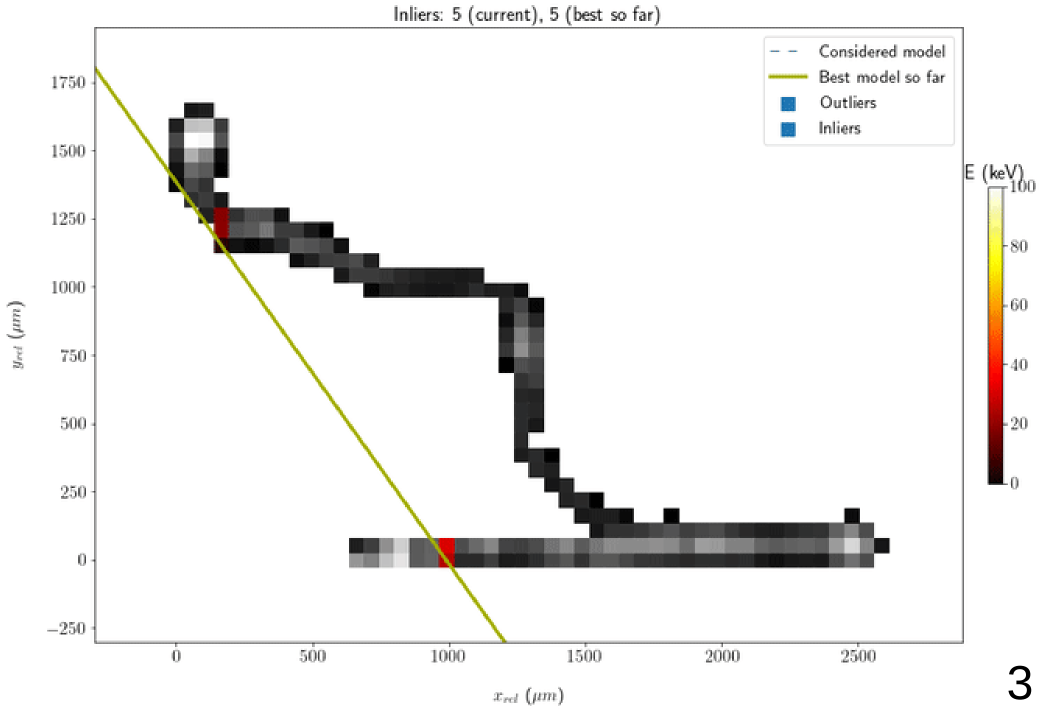
Trajectory estimation

- Why?
  - To determine where ionizing particles come from.
  - To separate particles in complex interactions.

- How?
  - Particles with sufficient energy produce linear tracks.
  - Assuming 1 particle per track, we fit a line with least squares.
  - Are we done? ☺
  - No, because of … random noise, overlaps, δ-rays, etc.
  - Solution: *robust fitting!*

Robust trajectory estimation

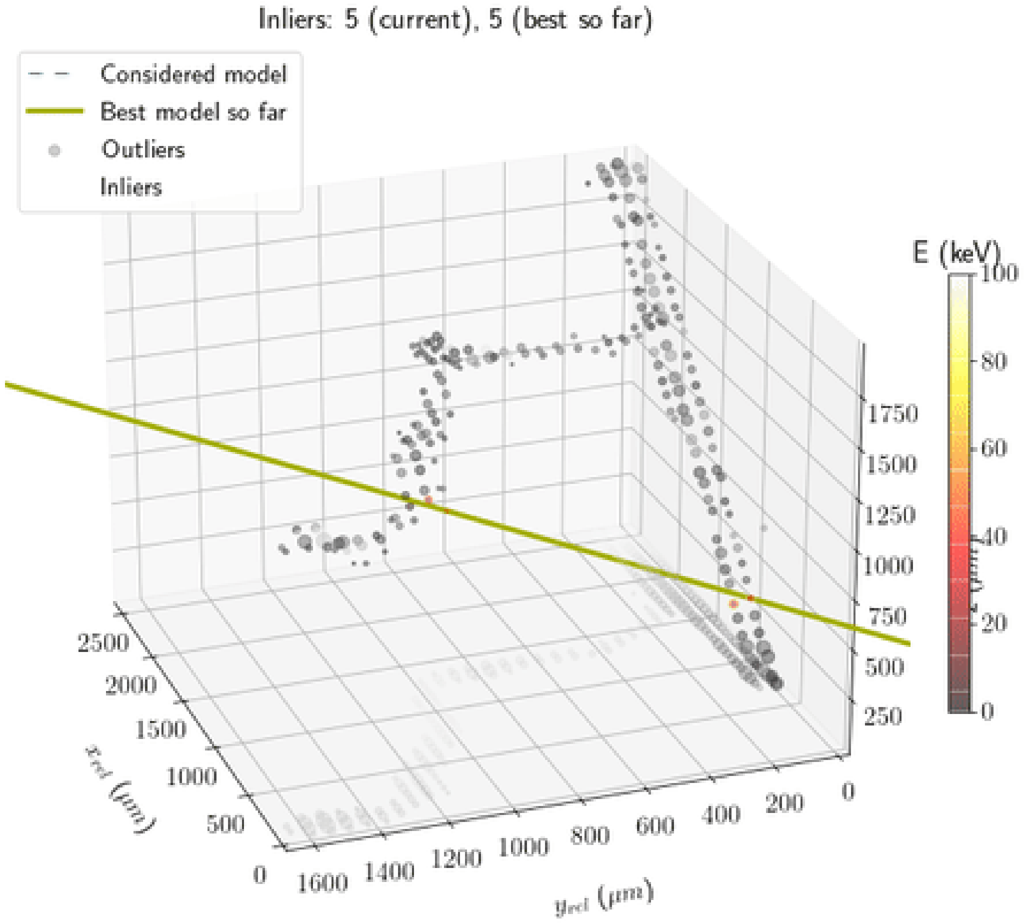
- From CV: Random sample consensus (RANSAC)
  1. Sample lines from the data at random.
  2. For each line, count hits closer than a threshold.
  3. Remember the line with the most hits.



- Advantages:
  - Fast, easy to implement & generalize,
  - Estimates P(incorrect sampling),
  - Copes with ≤ 50% outliers.
- Improvement: weighting by energy.

Mánek et al.: *Randomized Computer Vision Approaches for Pattern Recognition in Timepix and Timepix3 Detectors*, arXiv:1911.02367

Example: RANSAC in 3D



Bergmann et al.: *3D reconstruction of particle tracks in a 2 mm thick CdTe hybrid pixel detector*, EPJC 79/2, pp. 165

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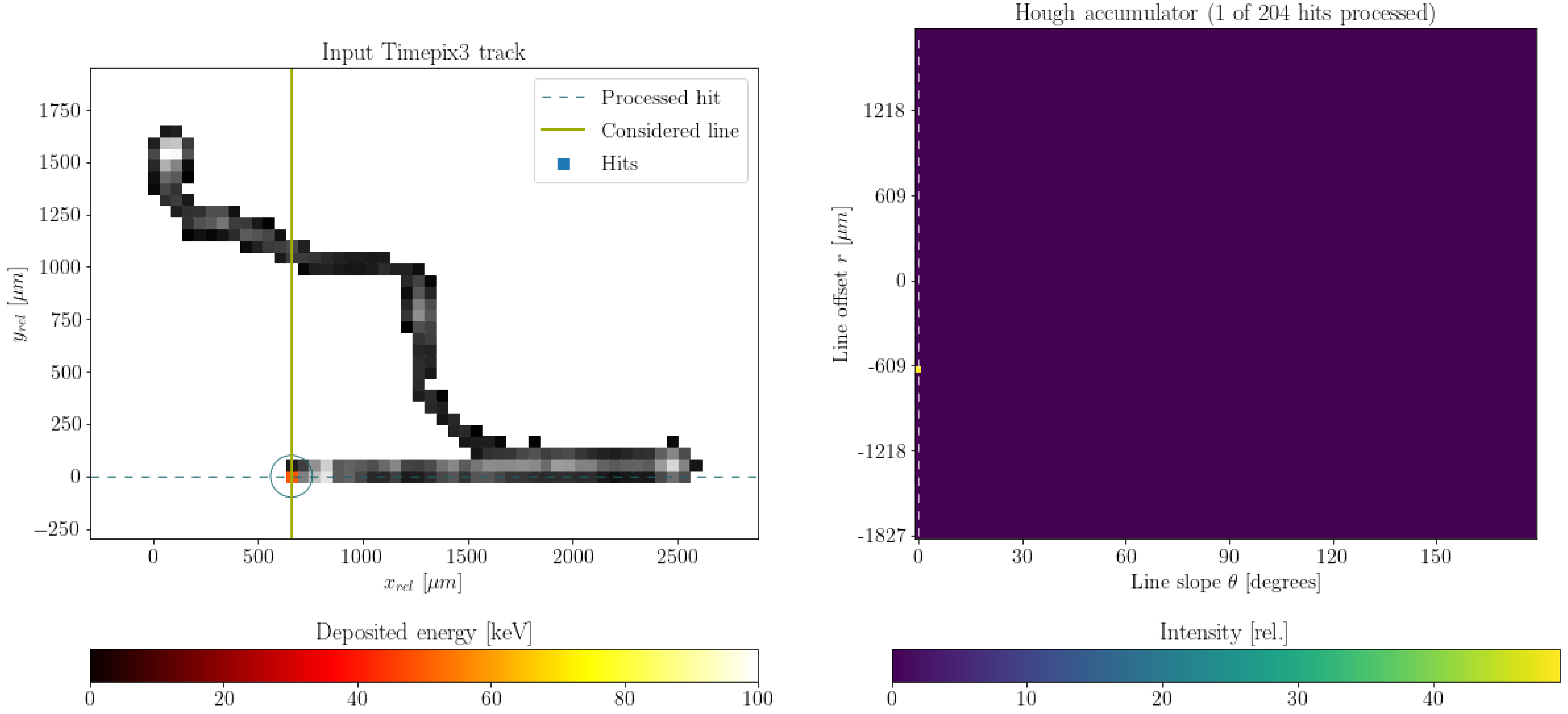
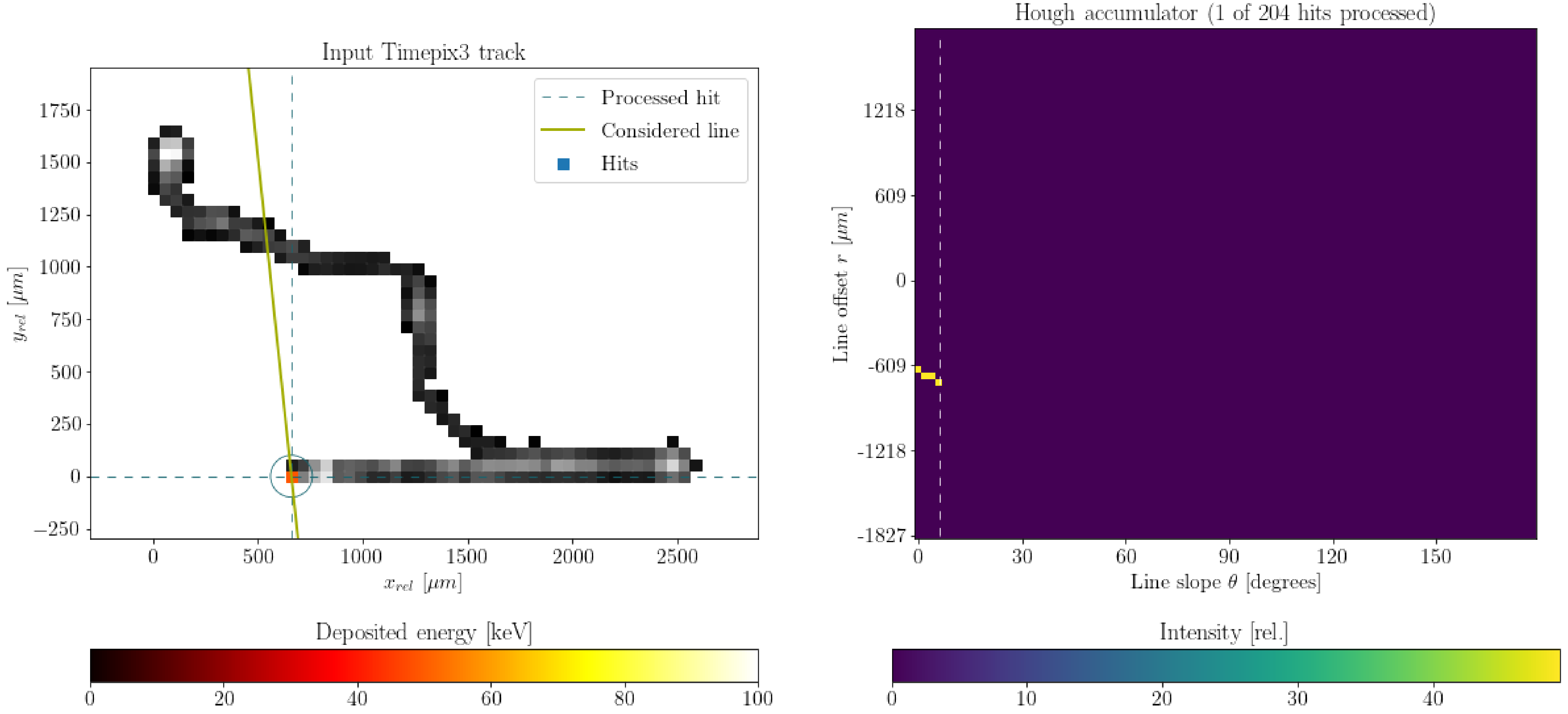
Example: Hough transform



Example: Hough transform



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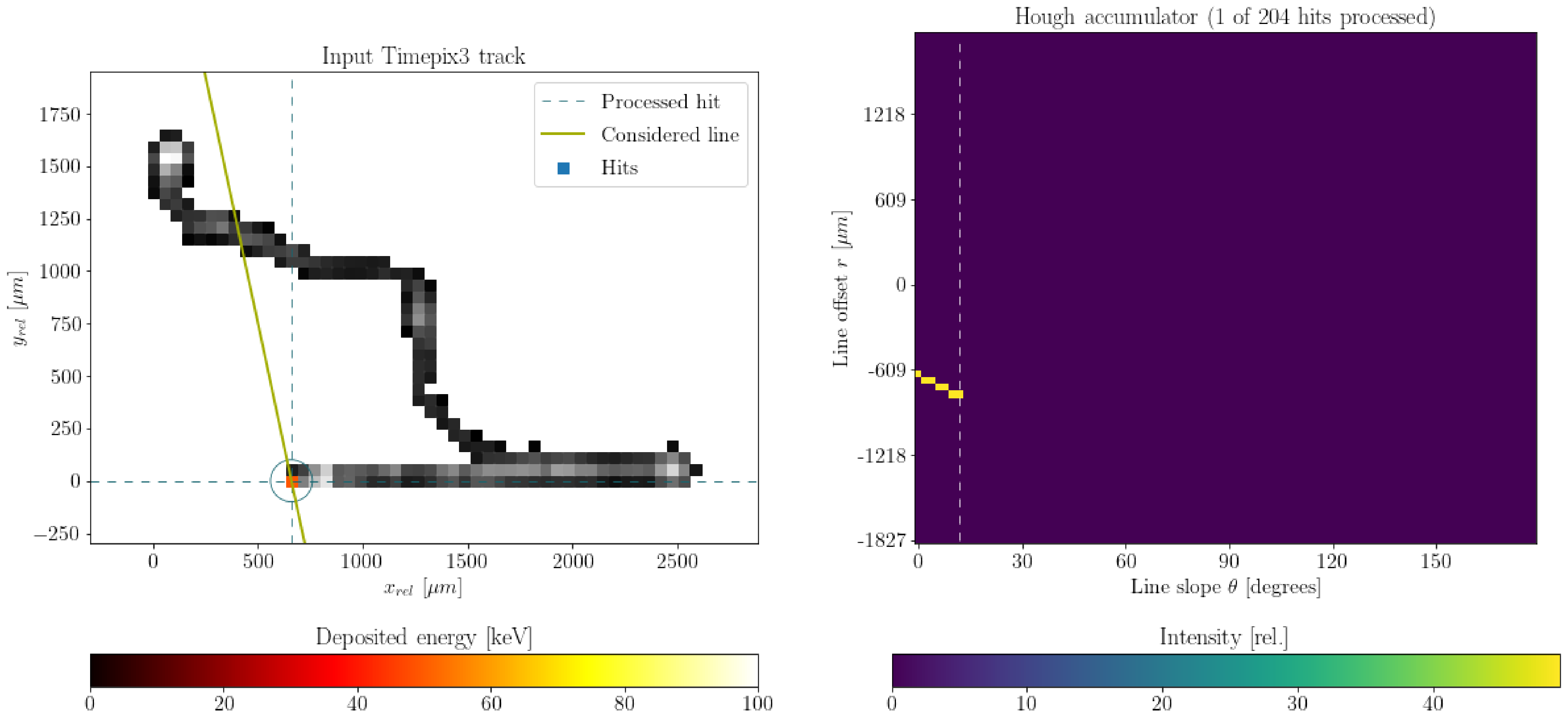
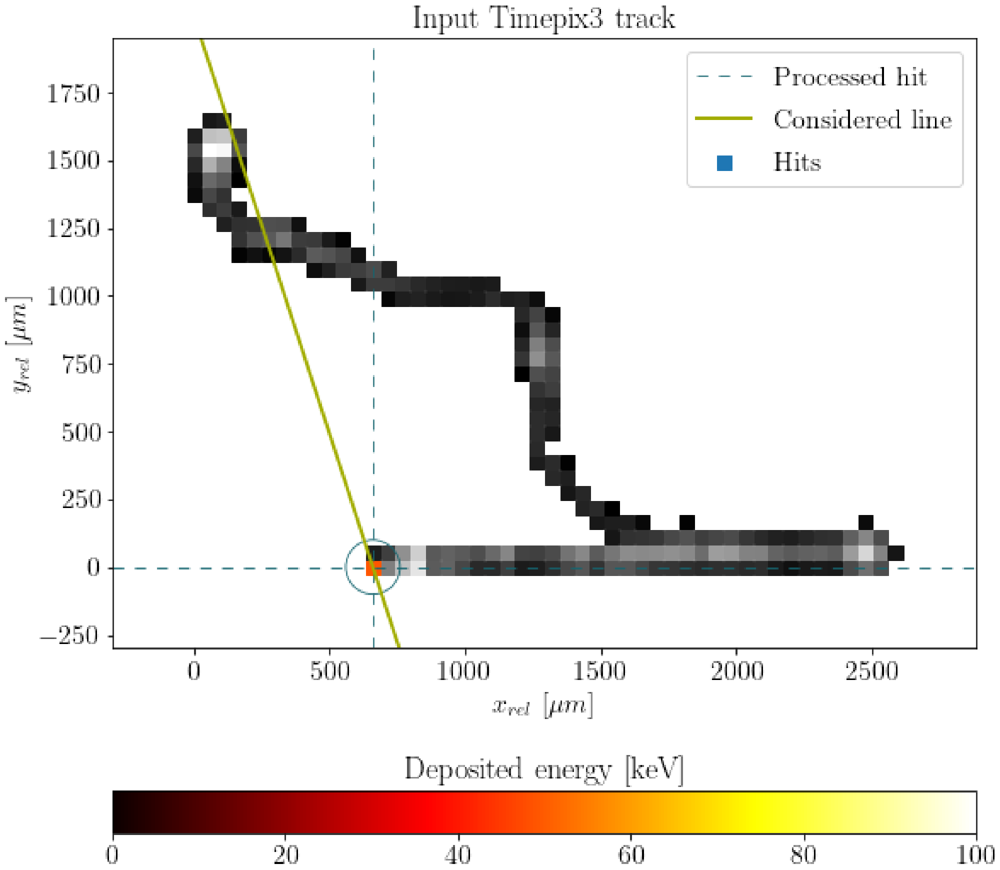
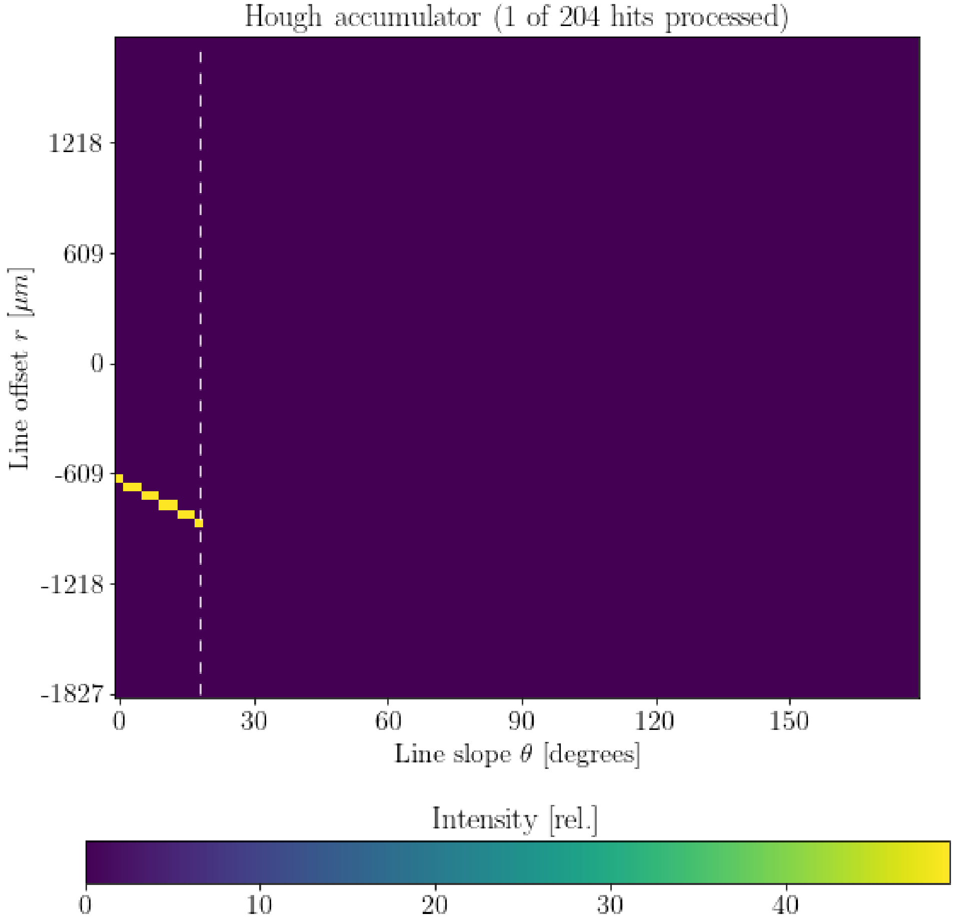


Example: Hough transform





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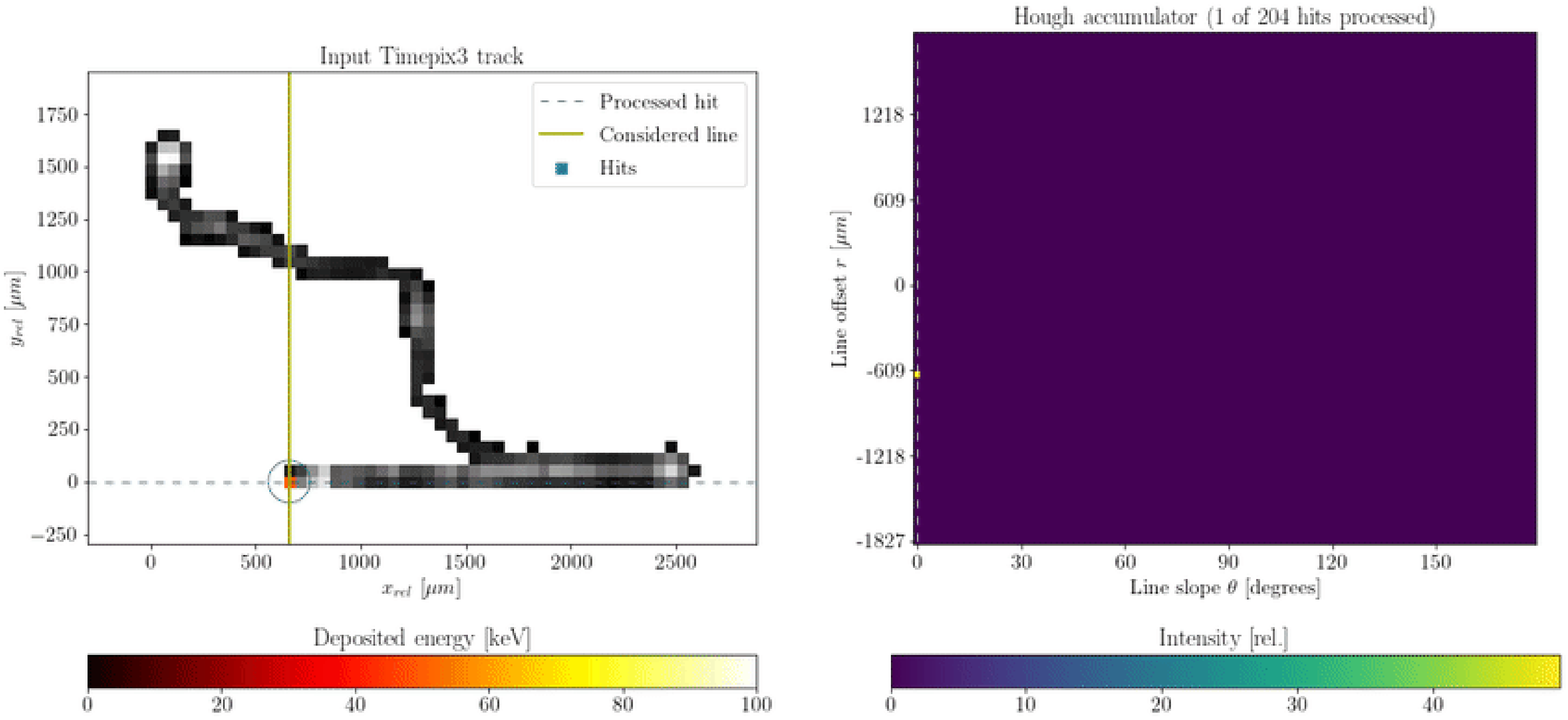
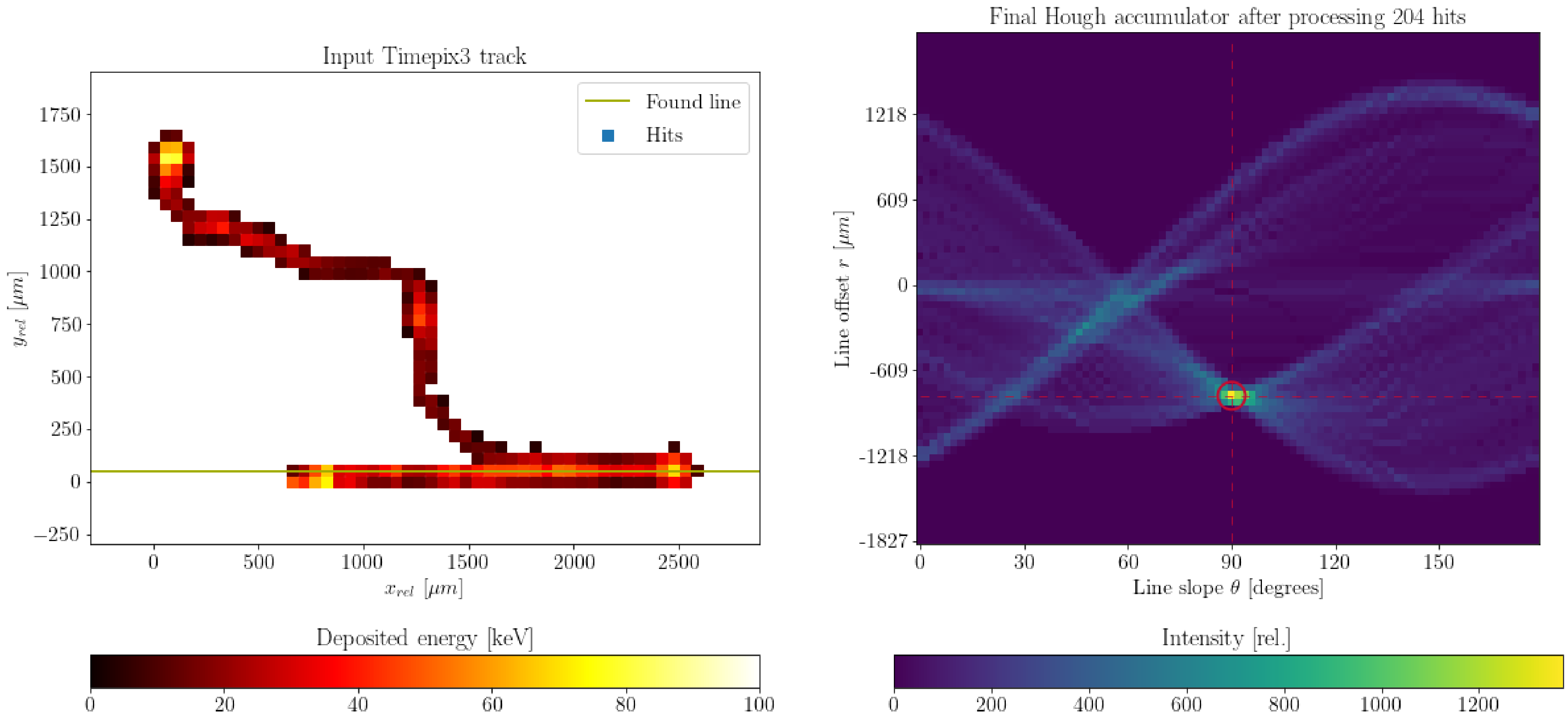
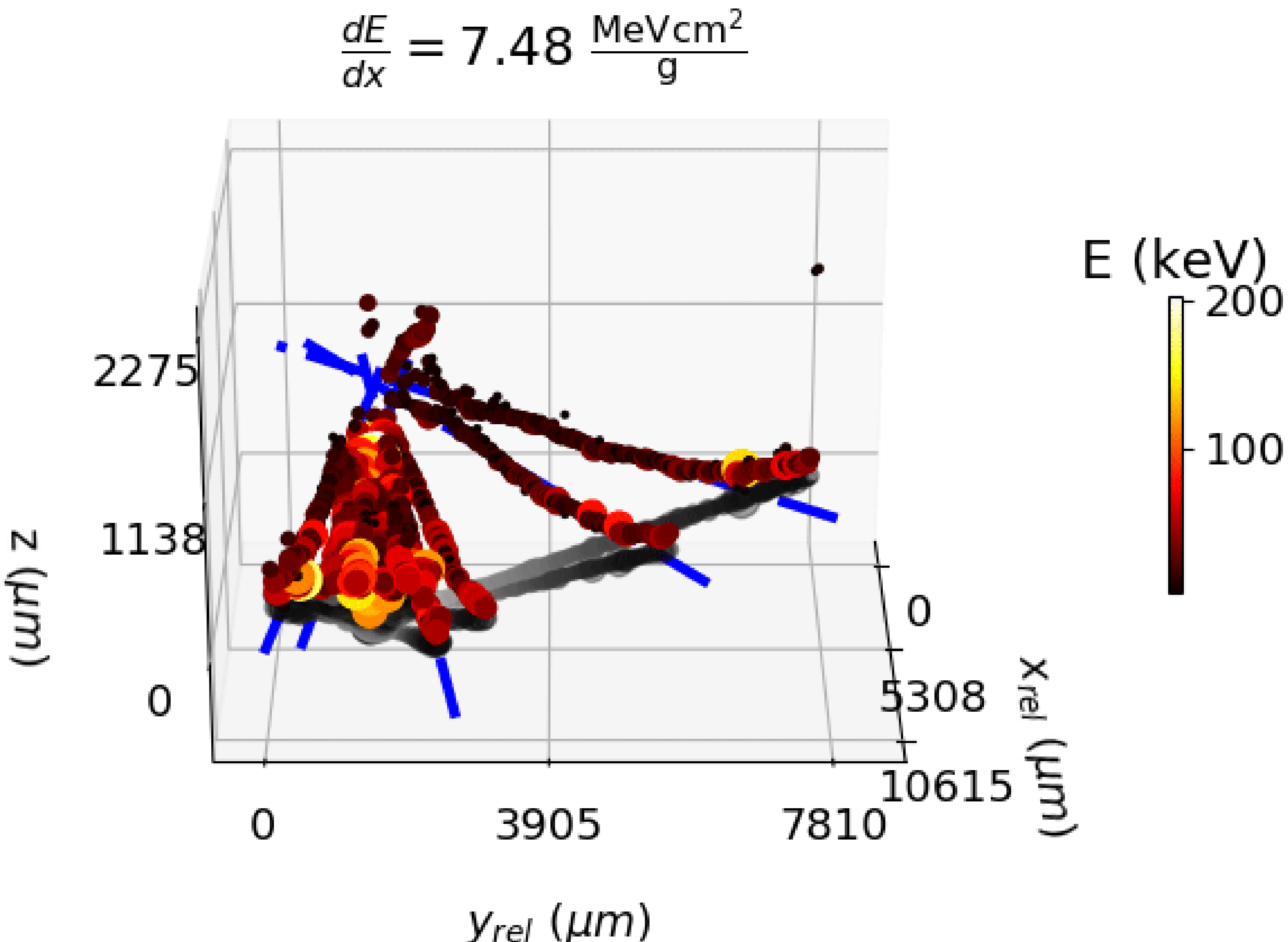


Example: Hough transform



Example: Hough in 3D



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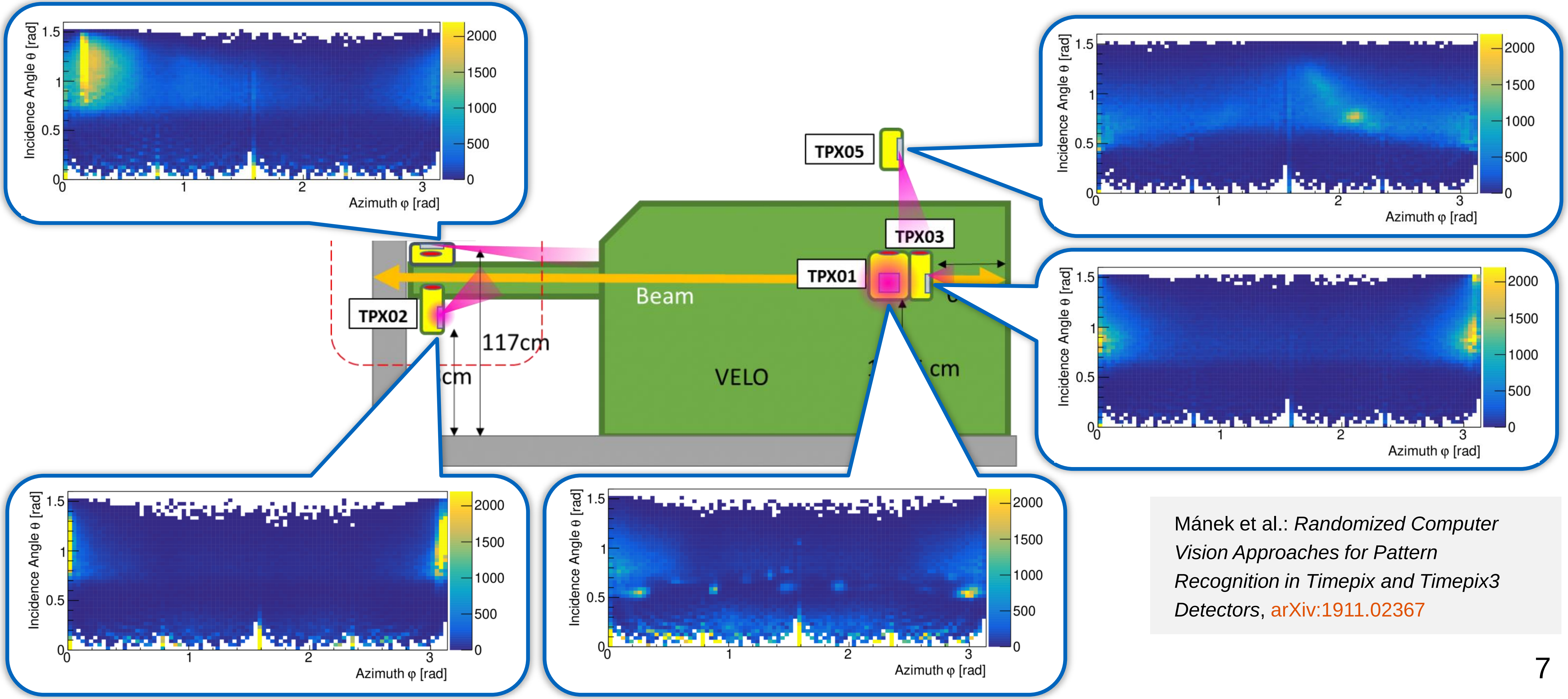
Example: MoEDAL directions



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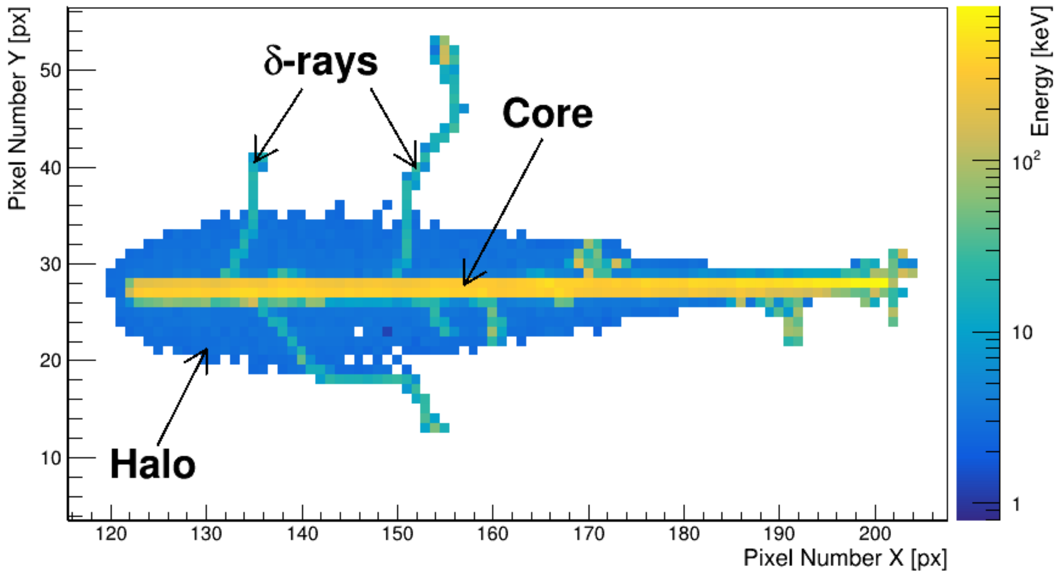
Particle identification – why?

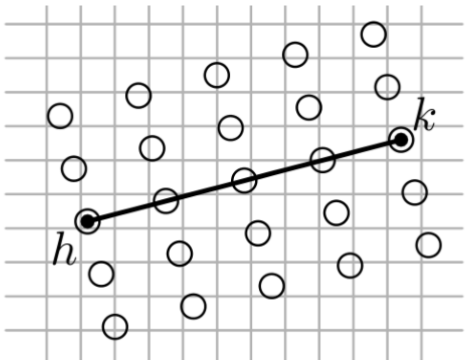
- Why?
  - To characterize unknown radiation fields.
  - To recognize (& compare) sources with known decay products.

- How? *Machine learning!*
  - We pre-process tracks into feature vectors (e.g. E, shape, complexity).
  - Or just train a neural net from a 2-channel image!

Ion classification

- Ions of different elements deposit energy at various rates (dE/dx).
- Procedure:
  1. Find & separate ion core.
  2. Sample energy along its path.

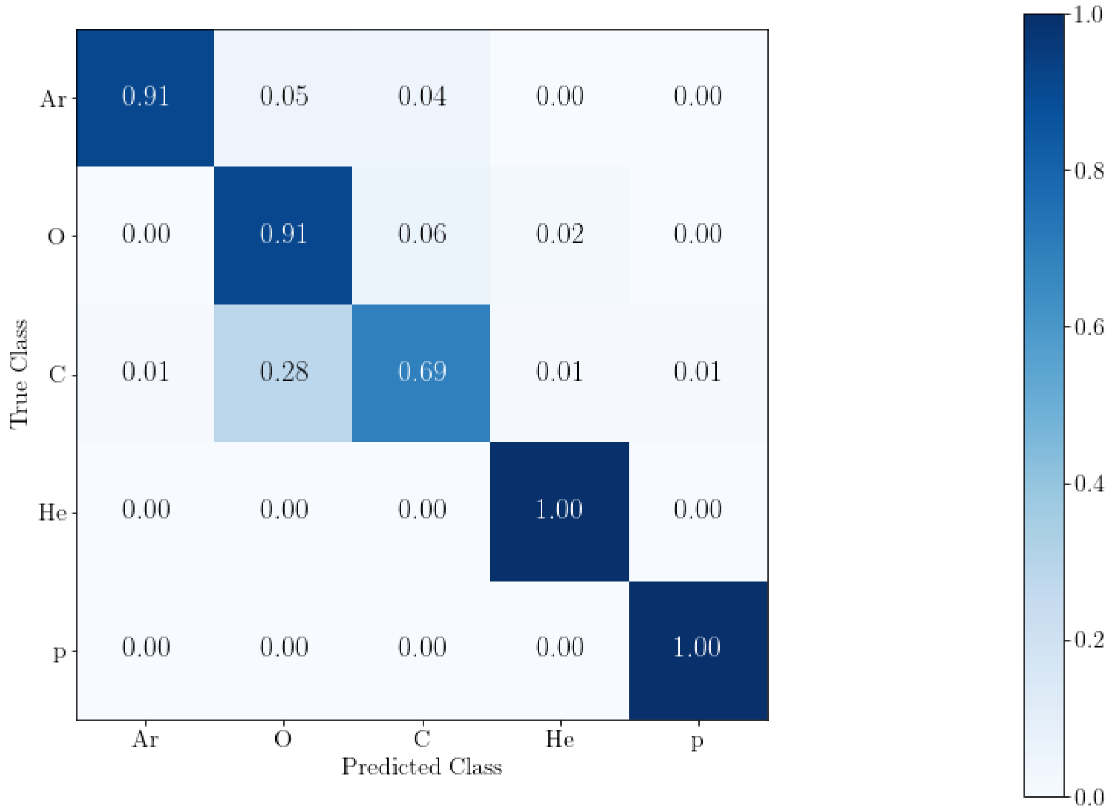




Mánek: *Machine learning approach to ionizing particle recognition using hybrid active pixel detectors*, FEE CTU Master's thesis, 2018

Ion classification

- Ions of different elements deposit energy at various rates (dE/dx).
- Procedure:
  1. Find & separate ion core.
  2. Sample energy along its path.
- Learning:
  - Annotated ~1K tracks of 5 species.
  - Trained k-NN classifier (k = 7).
  - 89.3% accuracy.



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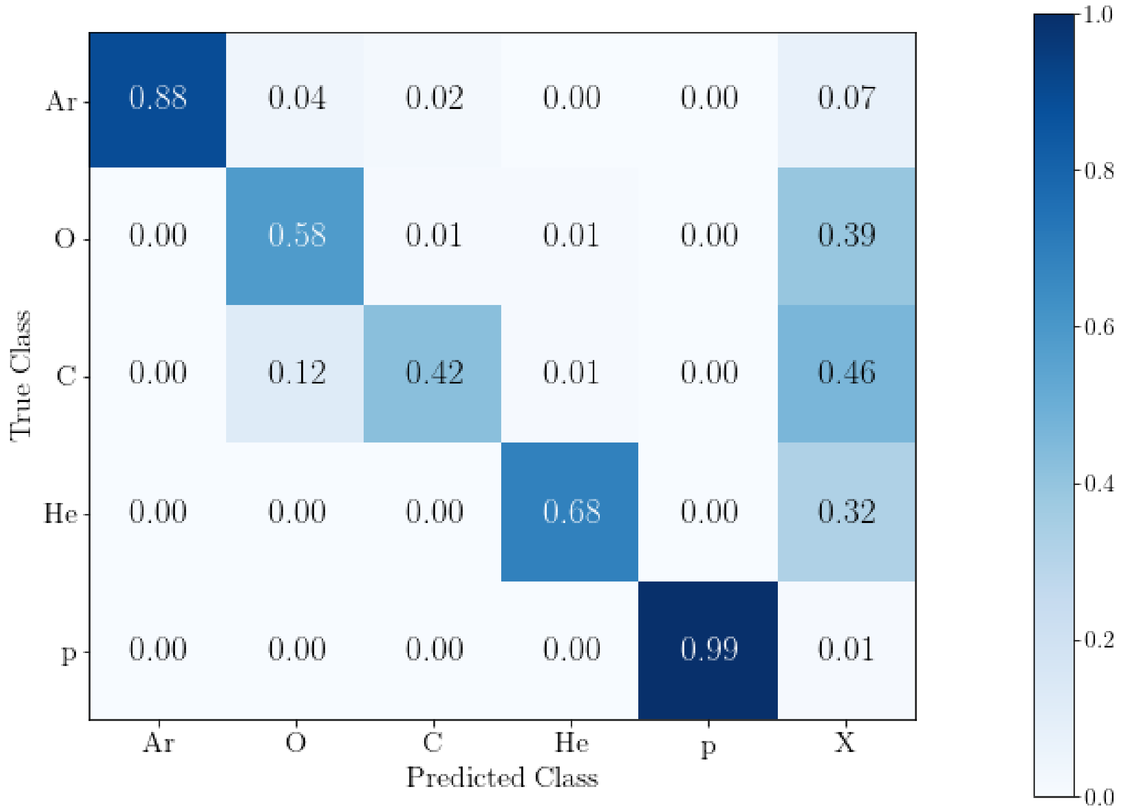
Ion classification (with rejection)

- Ions of different elements deposit energy at various rates (dE/dx).
- Procedure:
  1. Find & separate ion core.
  2. Sample energy along its path.
- Learning:
  - Annotated ~1K tracks of 5 species.
  - Trained k-NN classifier (k = 7).
  - New: reject if confidence < 90%.
  - 93.5% accuracy, ~25% rejected.



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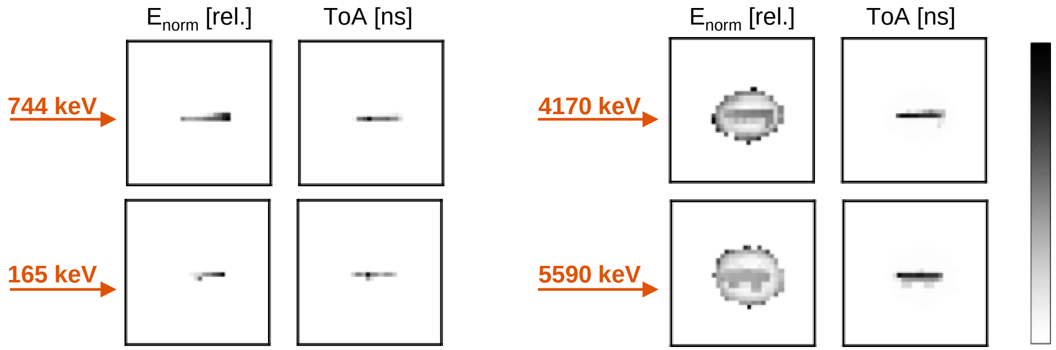
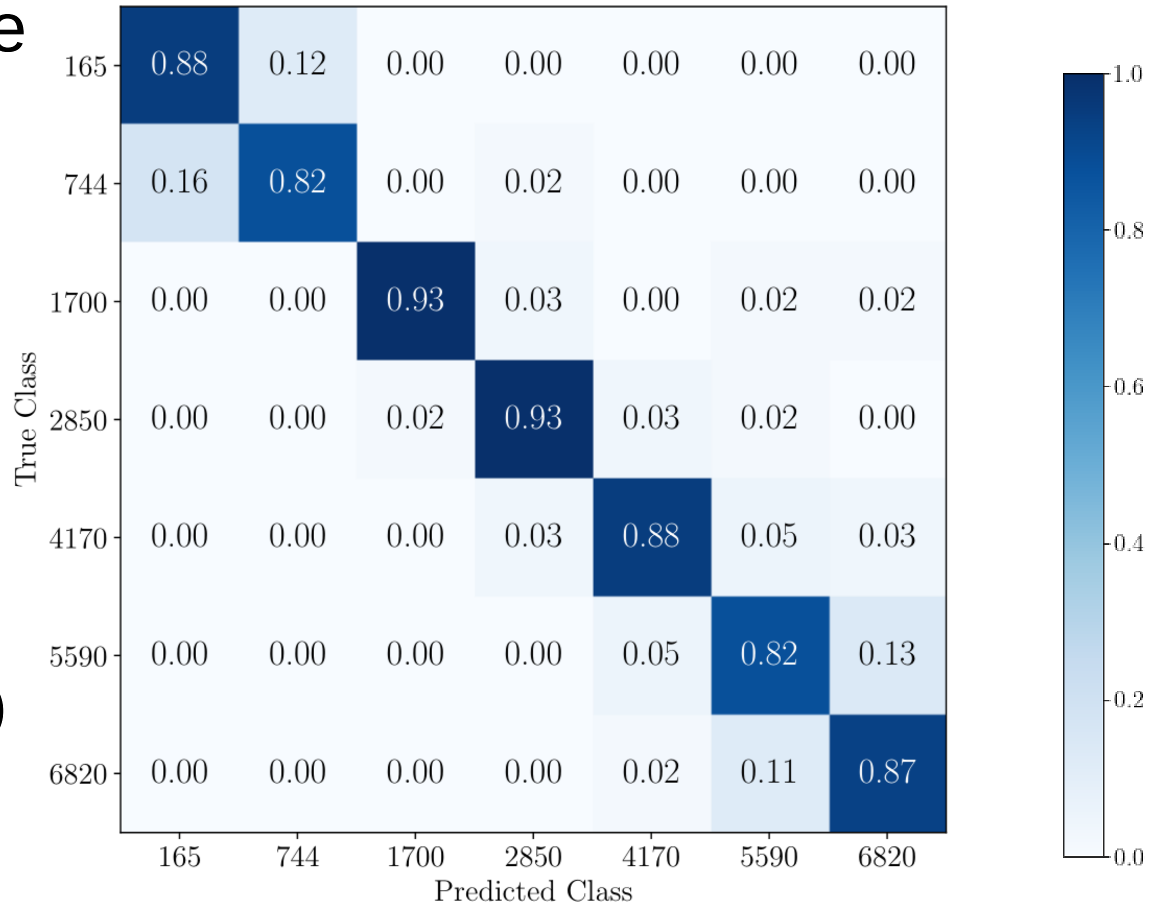
Ion momentum classification

- Tracks at different energy levels have characteristic shapes (e.g. halo).



- Procedure:
  1. Normalize tracks (in E, direction).
  2. Train a multi-layer perceptron (1×128) on pixel image (2×32×32).
- 87.7% accuracy.



Conclusion

- Timepix3 energy and time-of-arrival response encodes incident particle information in complex manner.
- Classifier models can be successfully trained for inference of particle properties.
- Robust computer vision methods are viable and tractable means of pre-processing Timepix3 data in 2D and 3D.
- Many avenues still remain to be explored!

Thank you for listening!

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