The untapped power of AI for tracking solar wind flows

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Special thanks to the PUNCH Team

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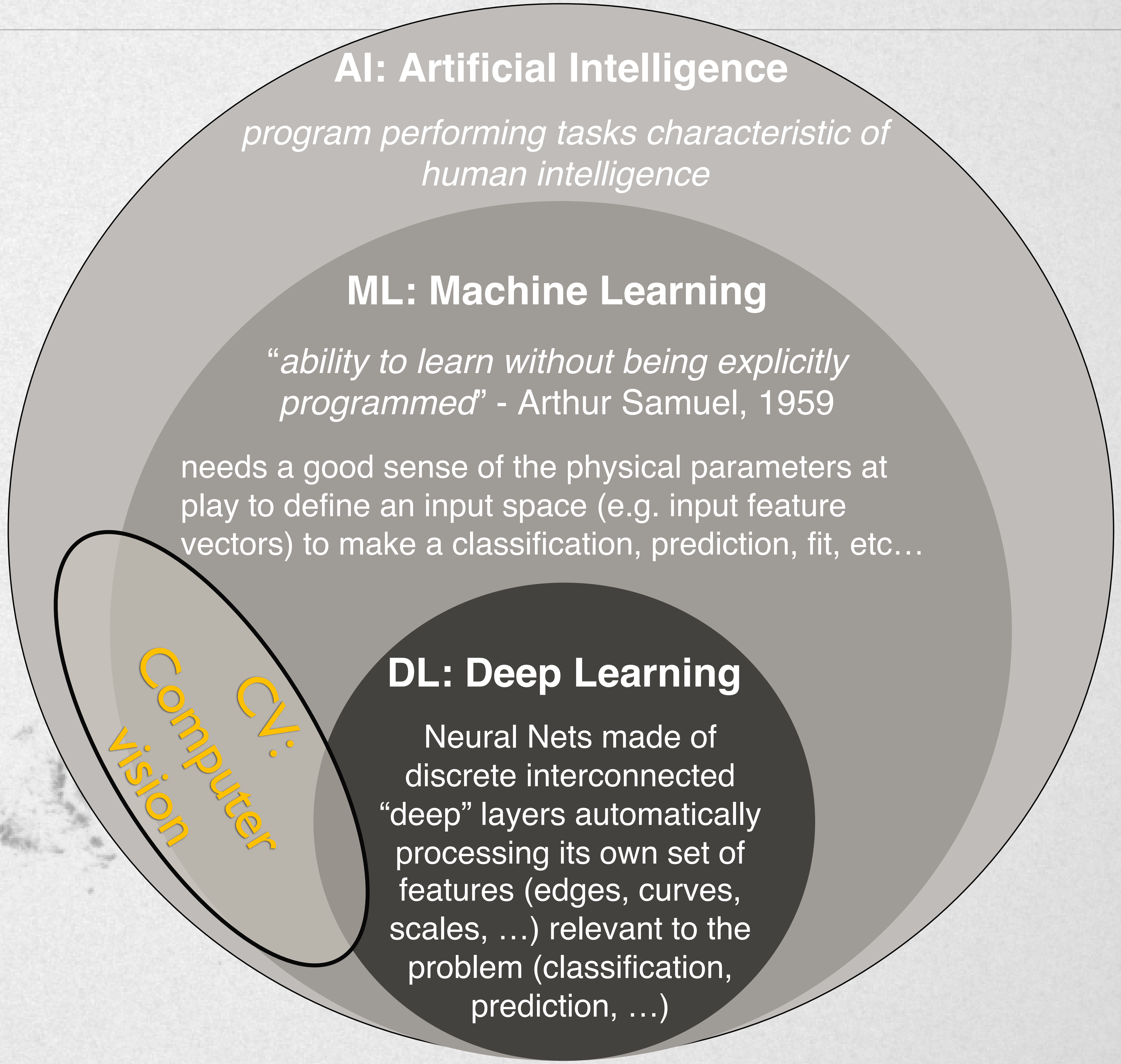
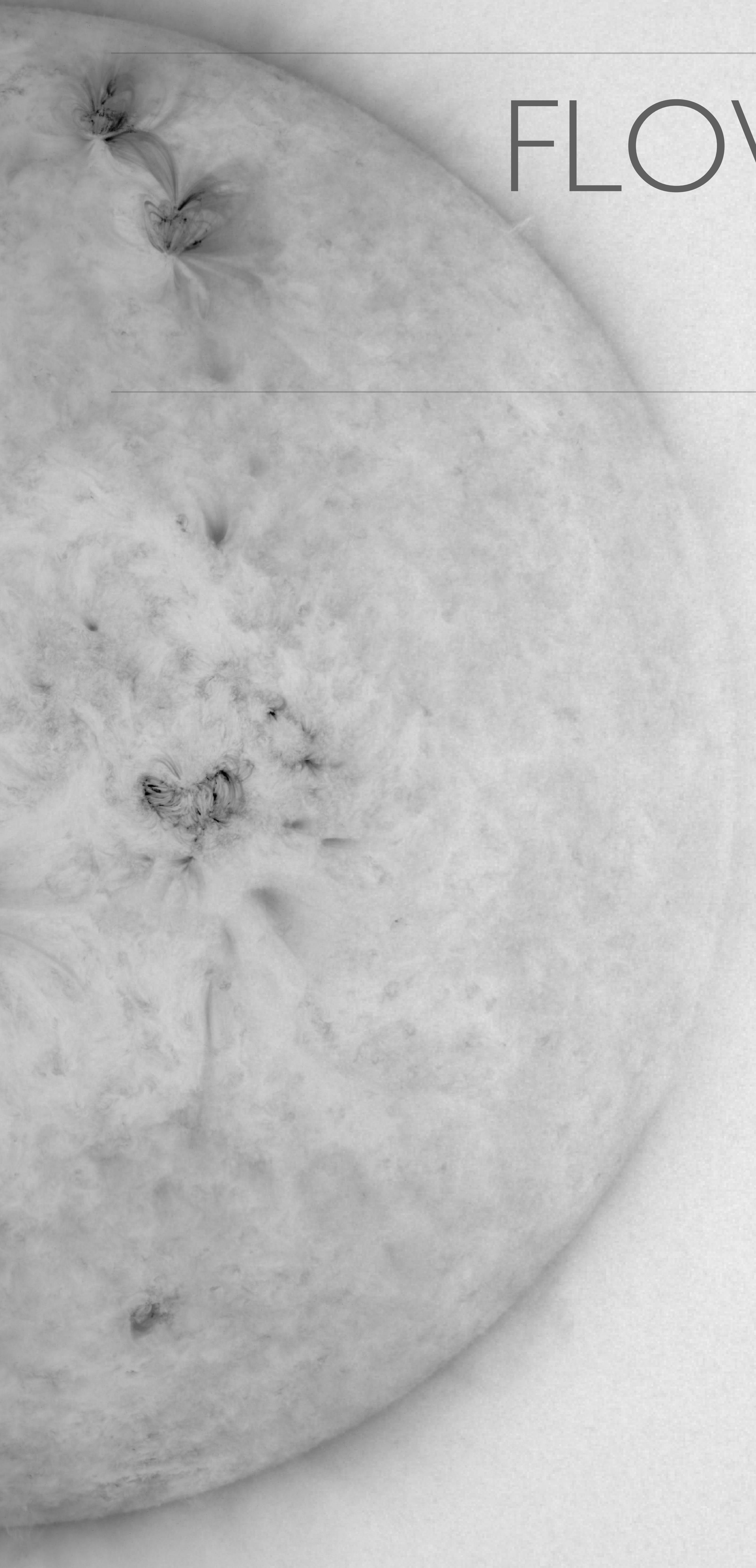
PUNCH Science Meeting 2– Aug 10, 2021

INTRODUCTION

AI, ML, DL, …, CV!



Tracking solar wind flows with PUNCH will make use of **Computer Vision.** CV exists across different domains of AI by achieving the recognition and/or tracking of certain objects in image series using Machine Learning, Deep Learning, or simpler image processing workflows.



FLOW TRACKING METHOD WITH CV: OPTICAL FLOWS

From Wikipedia: *Pattern of apparent motion of objects, surfaces, and edges in a visual scene caused by the relative motion between an observer and a scene…*

- Measured by a motion tracking algorithm
- Accuracy depends on the type of input imagery data and on the physical nature of the object being measured.
- Problem formally defines as:

$$I(x+\Delta x, y+\Delta y, t+\Delta t) = I(x,y,t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t$$

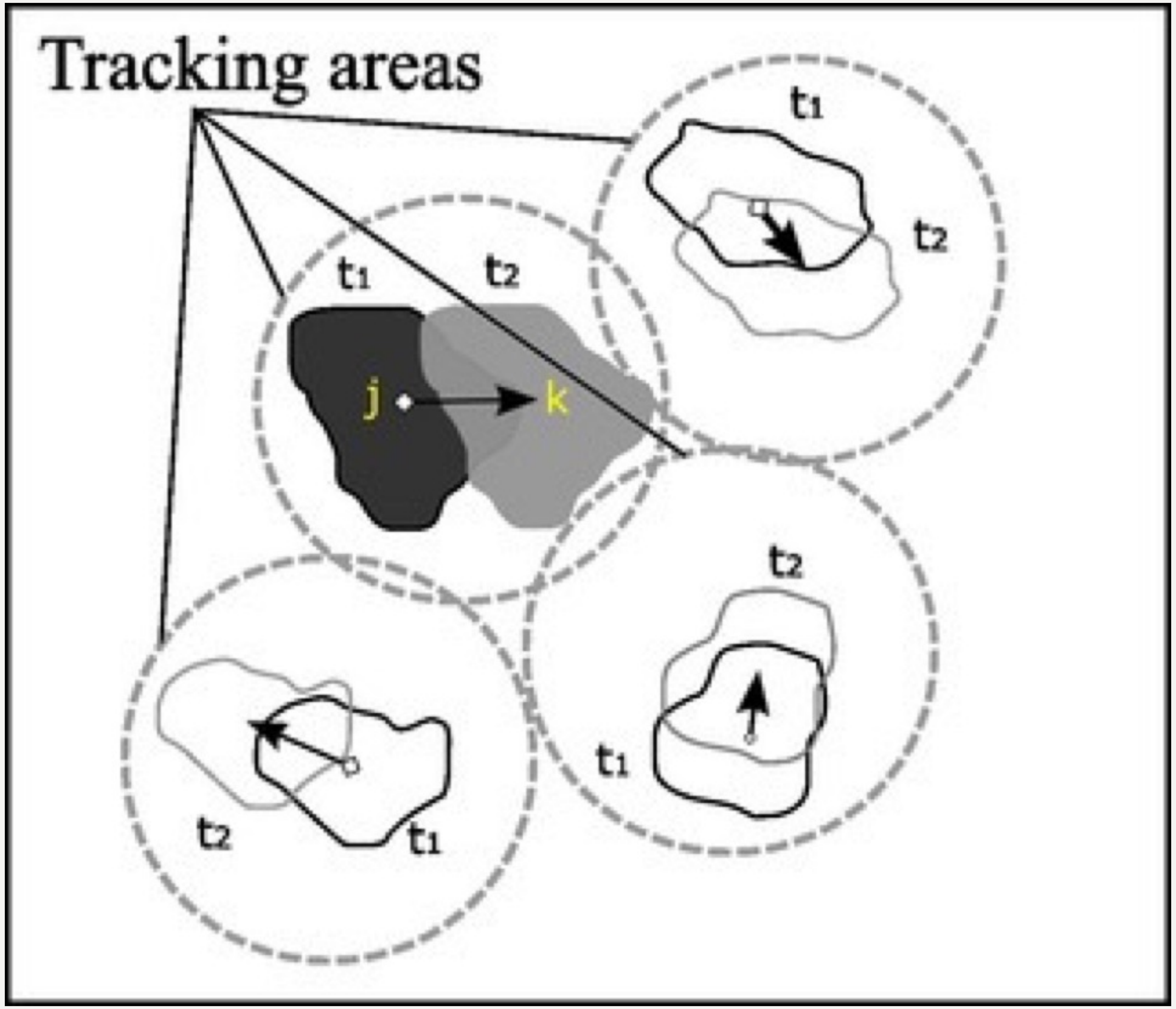
+ higher order terms

After linearization:

$$\frac{\partial I}{\partial x}\underbrace{\boxed{\frac{\Delta x}{\Delta t}}}_{Vx} + \frac{\partial I}{\partial y}\underbrace{\boxed{\frac{\Delta y}{\Delta t}}}_{Vy} + \frac{\partial I}{\partial t}\frac{\Delta t}{\Delta t} = 0$$

Additional constraints needed to solve for Vx and Vy

Principle of “Local Correlation Tracking”
(LCT, November & Simon, 1988)



Metric of similarity: correlation

$$\sigma_{X^f} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(X_i^f - \overline{X^f})^2}$$

$$R(k) = \frac{\sigma_{X^1X^2}}{\sigma_{X^1}\sigma_{X^2}}$$

$$R(k) = \frac{\sum_{i=1}^{N}\left[(X_i^1 - \overline{X^1})(X_{i+k}^2 - \overline{X^2})\right]}{\sqrt{\sum_{i=1}^{N}(X_i^1 - \overline{X^1})^2}\sqrt{\sum_{i=1}^{N}(X_i^2 - \overline{X^2})^2}}$$

LCT relies on the similarity metric of “correlation”, a number telling by how much two areas in consecutive images look alike. Among all possible displacements within a given window, the displacement of the feature (here, j -> k) is the one for which that number is maximum.

Optical flows

Exist in many flavors (Lucas – Kanade, Horn & Schunck, LCT, Fourier LCT). Perfect reconstruction of the plasma velocity not possible with optical flows. The mathematical formalism behind optical flows is very naive from the standpoint of Physics: there is no guarantee that the linearized optical flow equation has a physically meaningful solution.

$$I(x+\Delta x, y+\Delta y, t+\Delta t) = I(x,y,t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t$$

Optical flow approximation: never true

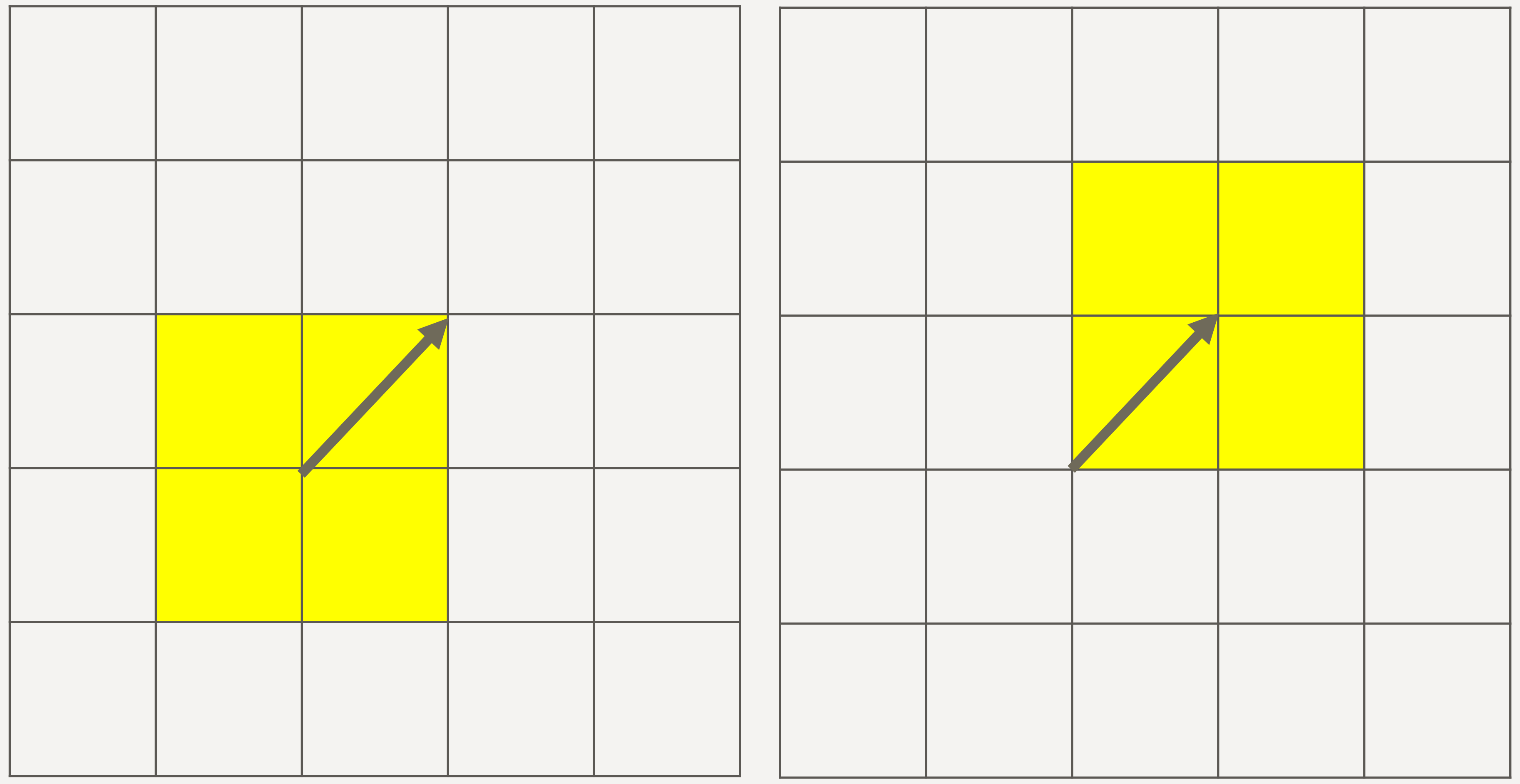
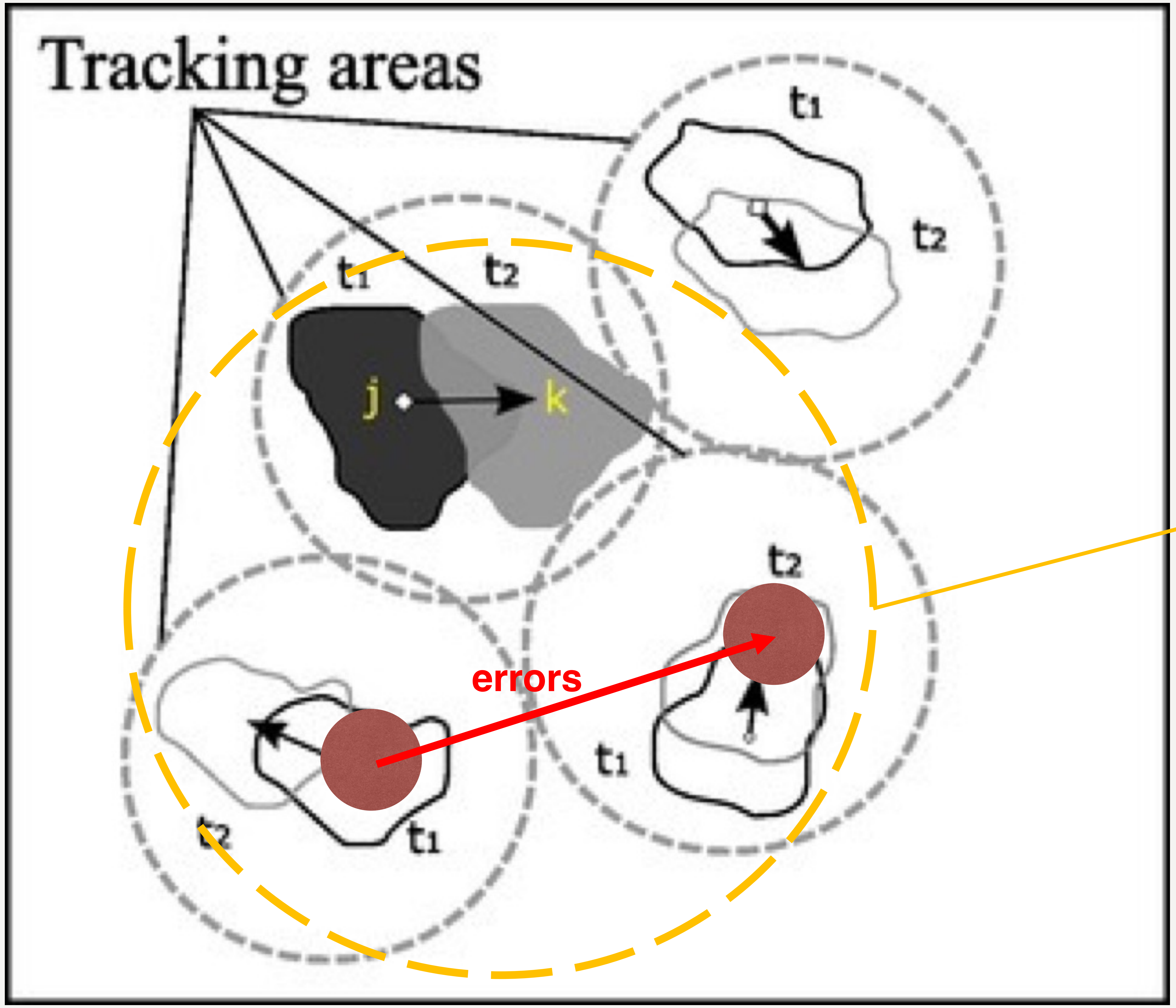
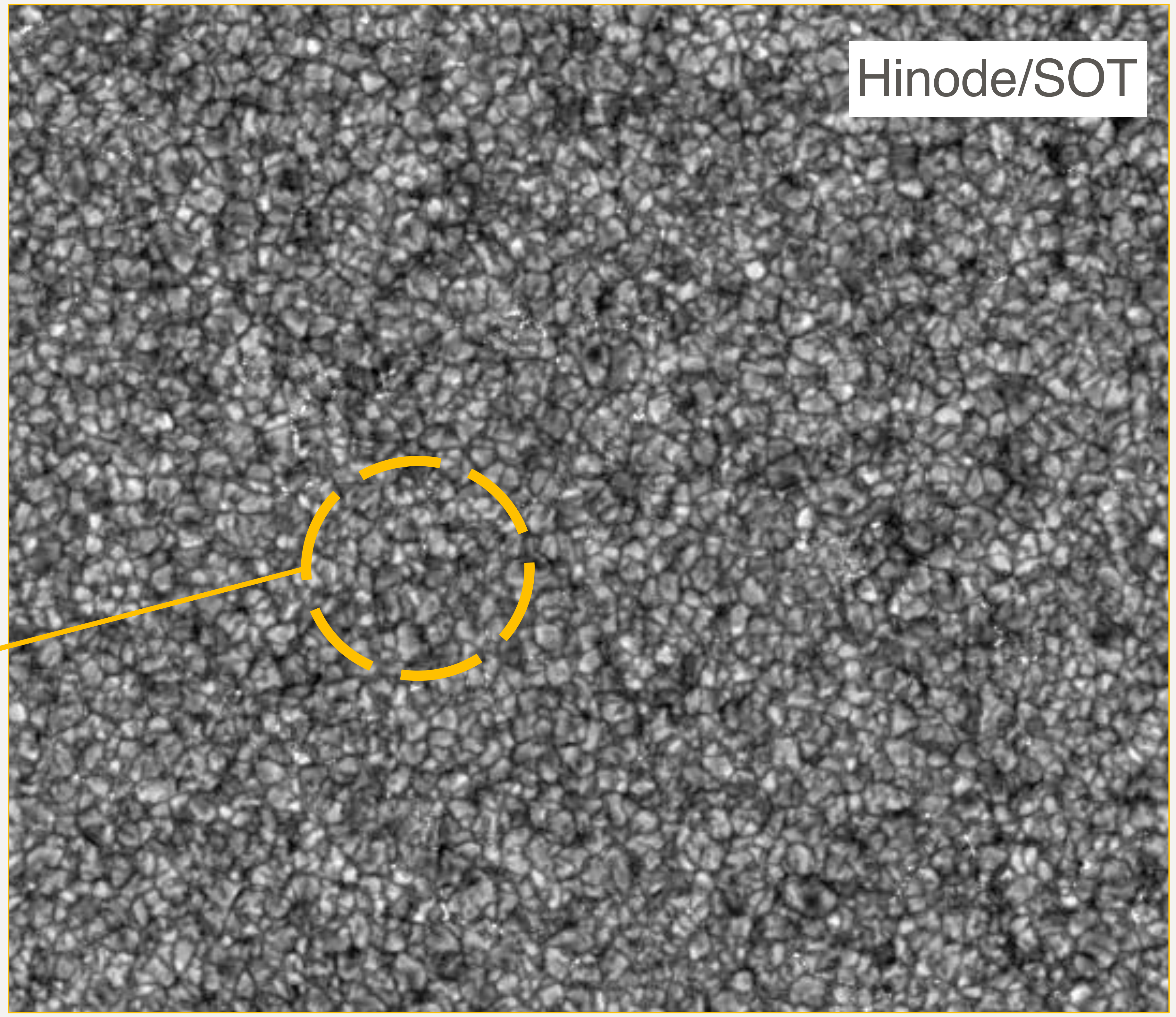


Image 1 at t

Image 2 at t + dt





In reality, the tracking window in which the brightness matching happens must be large enough to have a solution, but small enough to keep a decent resolution. It's a compromise and the matching process is often ambiguous (ill-posed problems).
Intensity regions (e.g. granules or PDS) can look similar enough to "fool" the matching process-> errors!

Optical flows

The mathematical formalism behind optical flows is very naive from the standpoint of Physics: there is no guarantee that the linearized optical flow equation even has a physically meaningful solution.

$$I(x+\Delta x, y+\Delta y, t+\Delta t) = I(x,y,t) + \frac{\partial I}{\partial x}\Delta x + \frac{\partial I}{\partial y}\Delta y + \frac{\partial I}{\partial t}\Delta t$$

STEREO/COR2 Deep-exposure campaign. *Courtesy of Craig Deforest*

With heliospheric imagery, without stereoscopy, what guarantee do we have that matching patterns at the next time step corresponds to the flow of a coherent density structure?

In fact, we do not:
=> source of many uncertainties

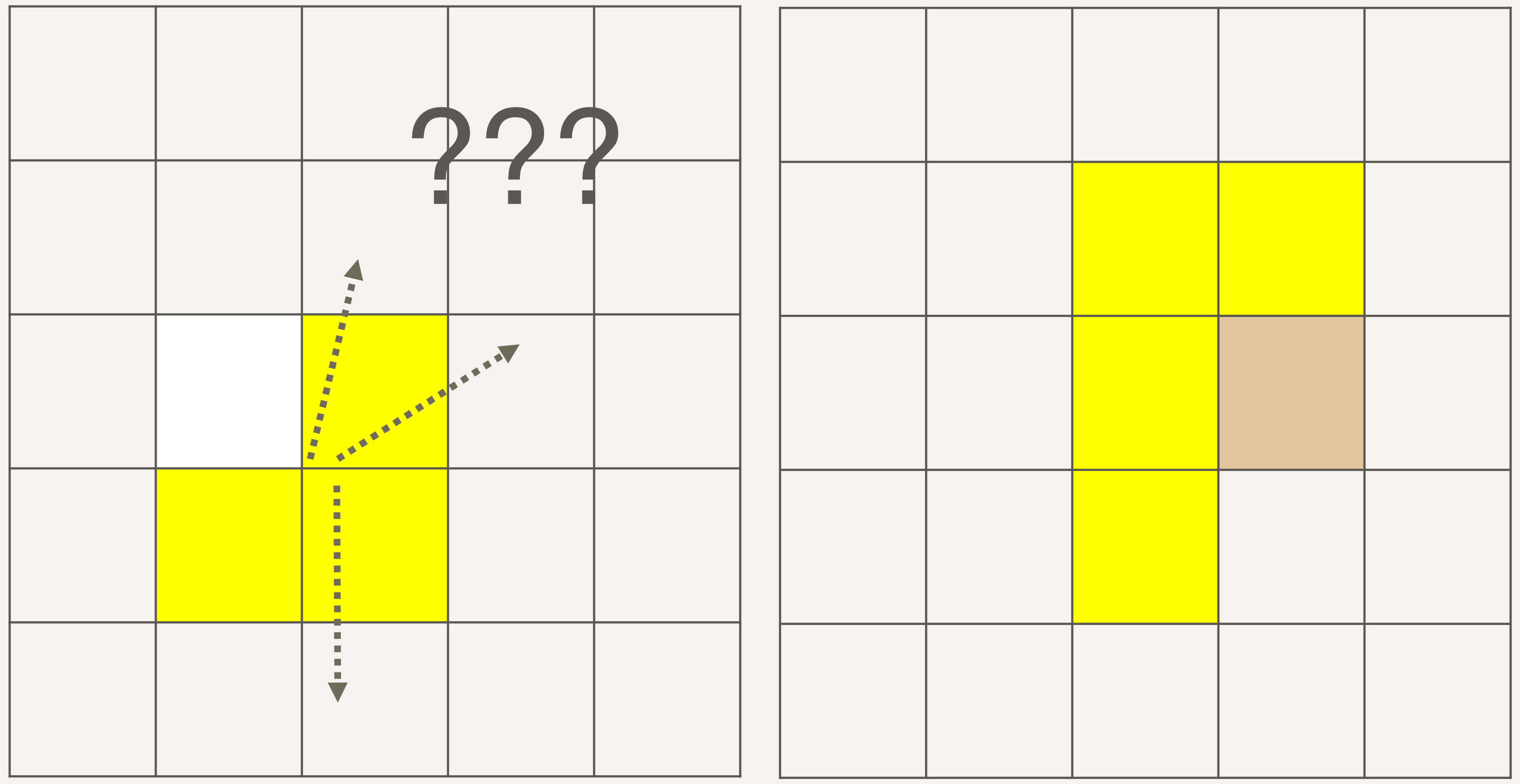


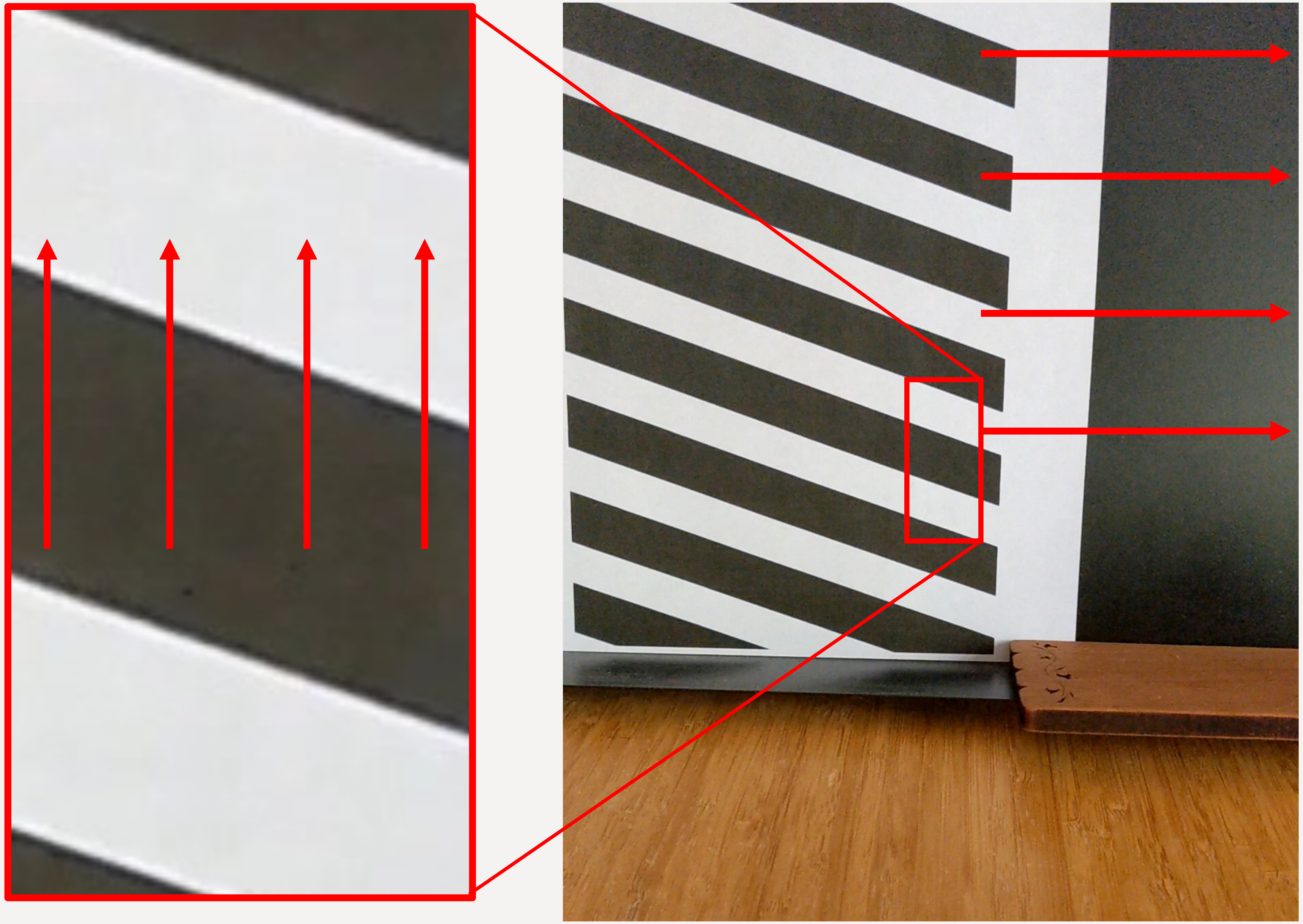
Image 1 at t

Image 2 at t + dt

Home-made experiment…

Optical flows track apparent motion…

The **aperture problem** refers to the ambiguity in determining the true velocity using a local motion detector.

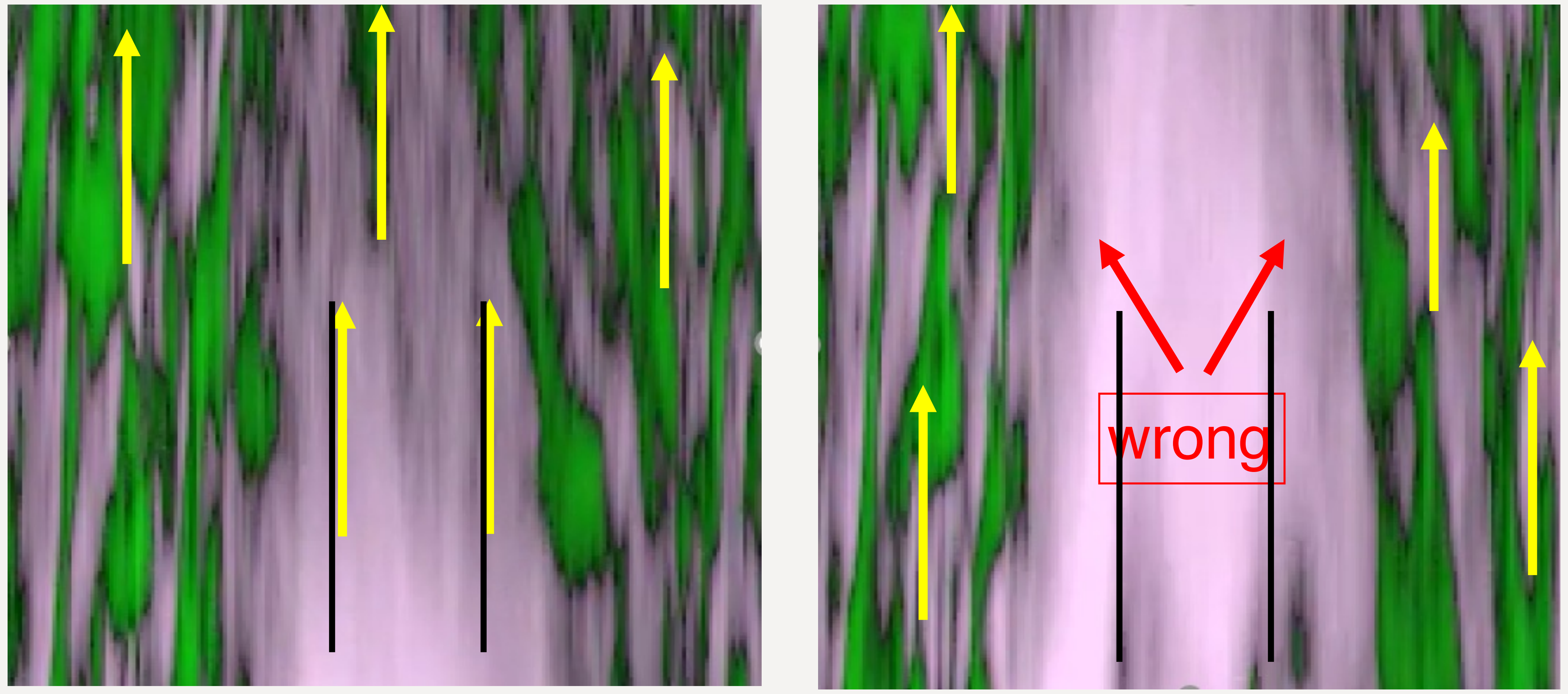


The **aperture problem** refers to the ambiguity in determining the true velocity using a local motion detector.

Image Credits: Matlab documentation: https://www.mathworks.com/help/supportpkg/parrot/ug/optical-flow-with-parrot-minidrones.html

Optical flows cannot provide flow information in the interior of uniform regions of the image

Background: STEREO/COR2 data. Deep Exposure campaign (courtesy of Craig Deforest)



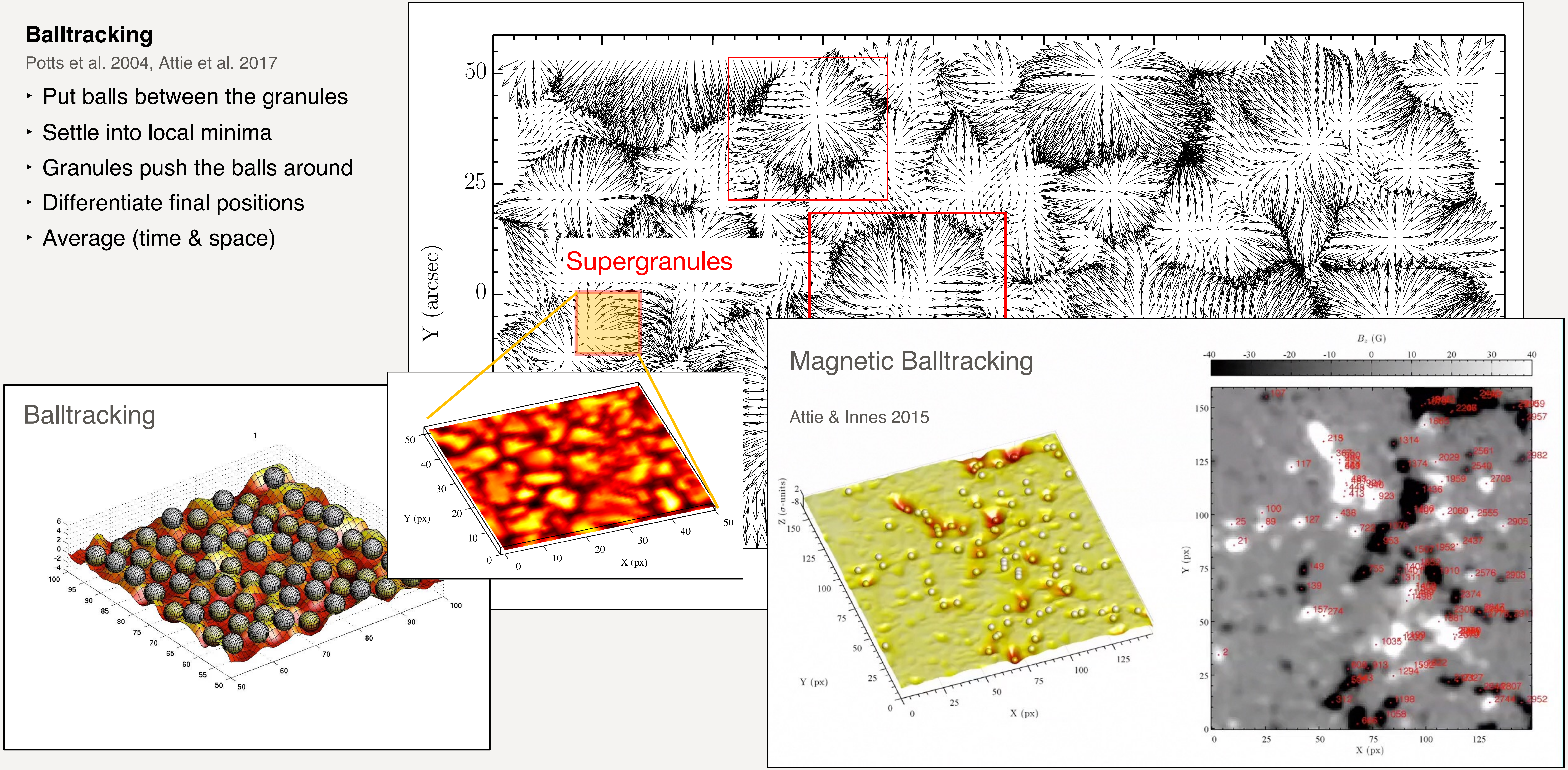
Propagation of a plasma density structure (purple) that has poor contrast, and whose horizontal dimension grows from top to bottom, revealing itself in the local subfield as it propagates only upward, can be interpreted as a lateral motion of plasma.

Tracking plasma momentum without similarity metric or pattern matching

Balltracking

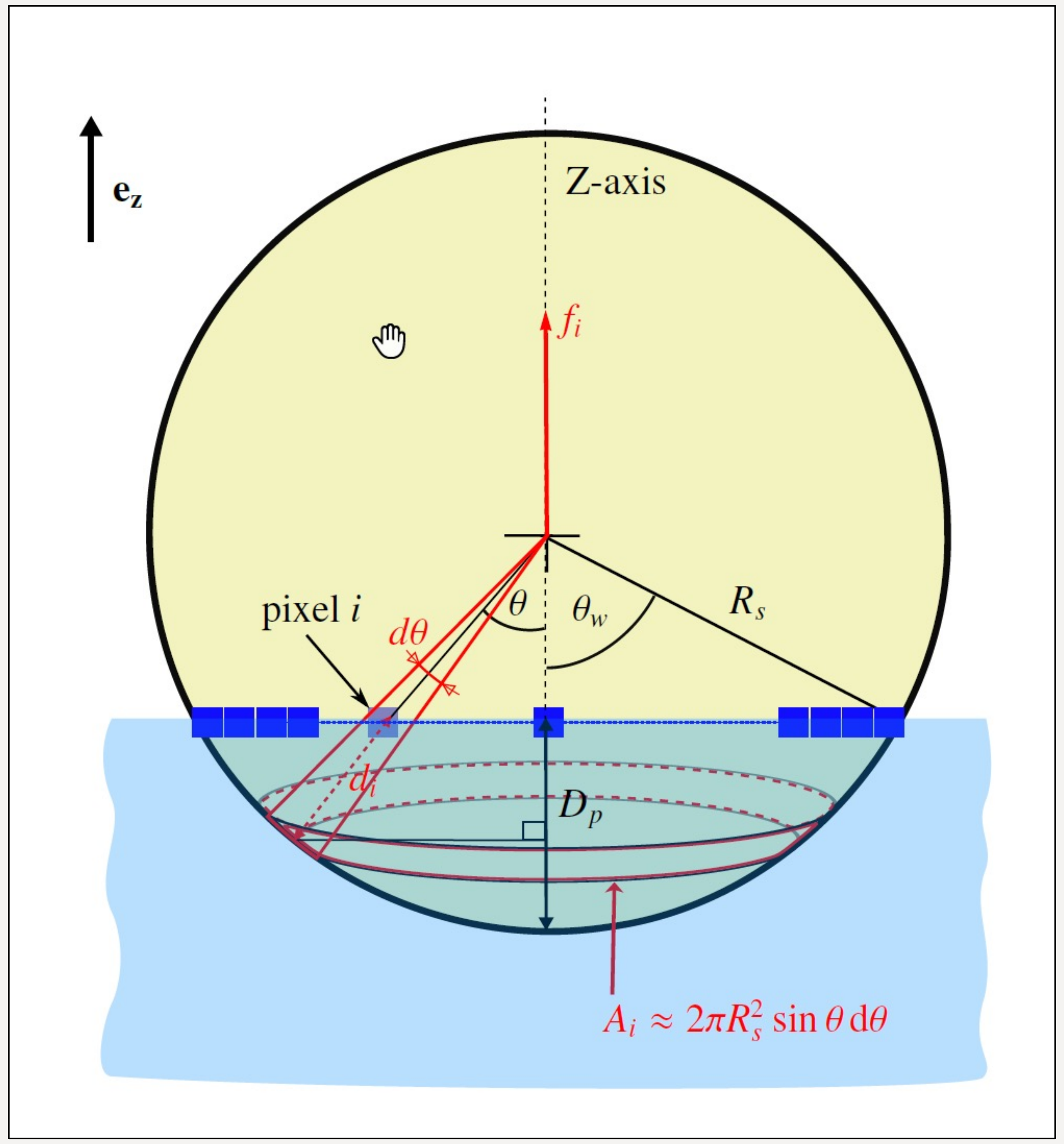
Potts et al. 2004, Attie et al. 2017

- Put balls between the granules
- Settle into local minima
- Granules push the balls around
- Differentiate final positions
- Average (time & space)



Alternative to optical flows

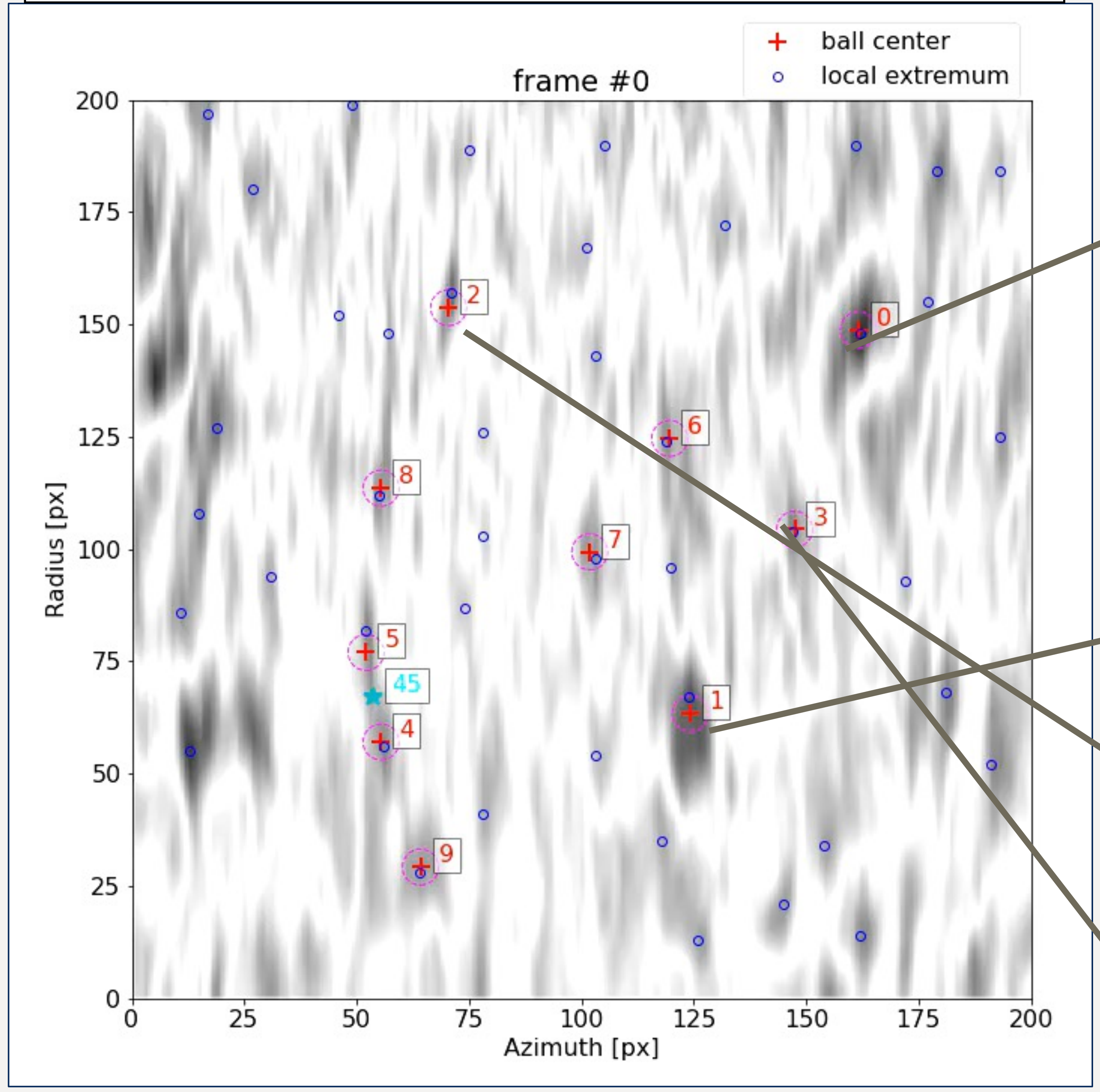
Magnetic Balltracking + ML



Parameters to learn:

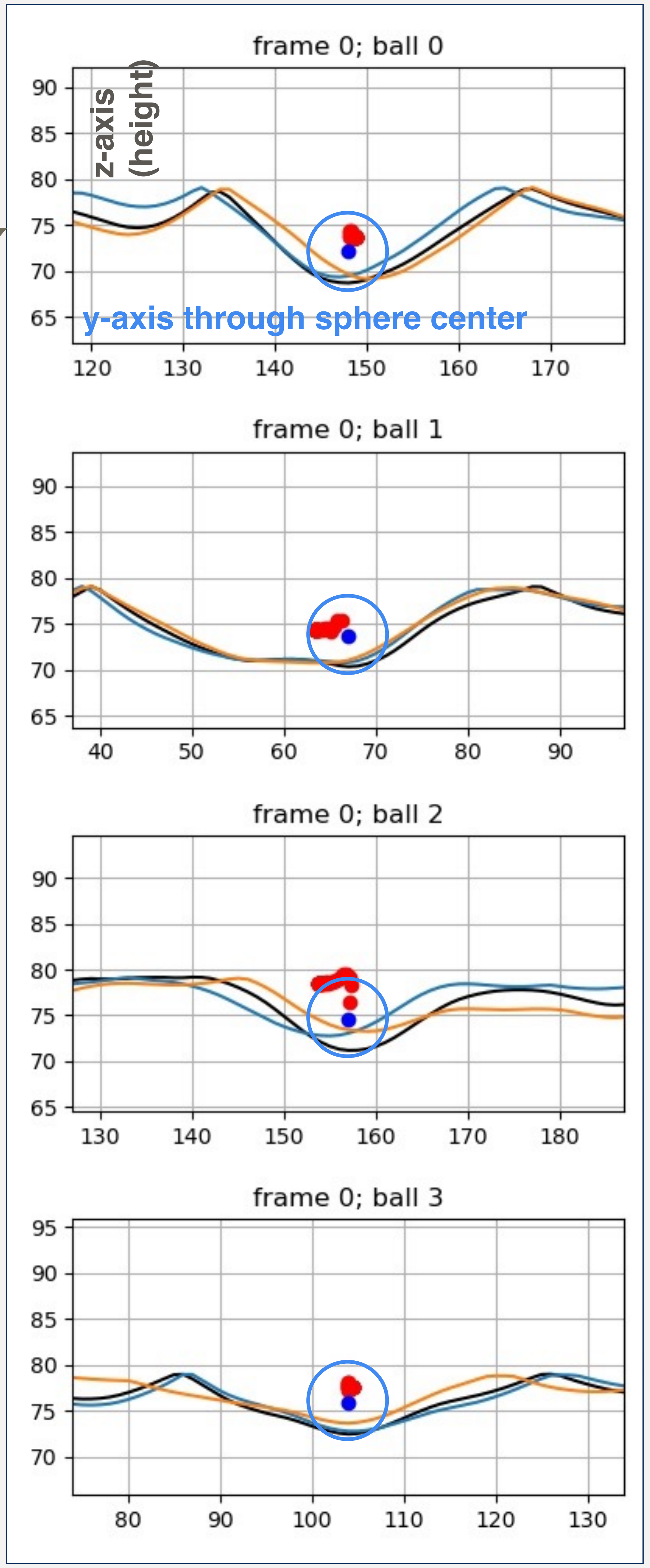
- multiplier to st. dev. for converting the intensity map to the data surface
- sphere radius
- “fluid” penetration parameter
- Acceleration modifier
- Damping time
- Nb of integration steps between images

Training and Cross-Validation set built with COR2 deep-exposure campaign

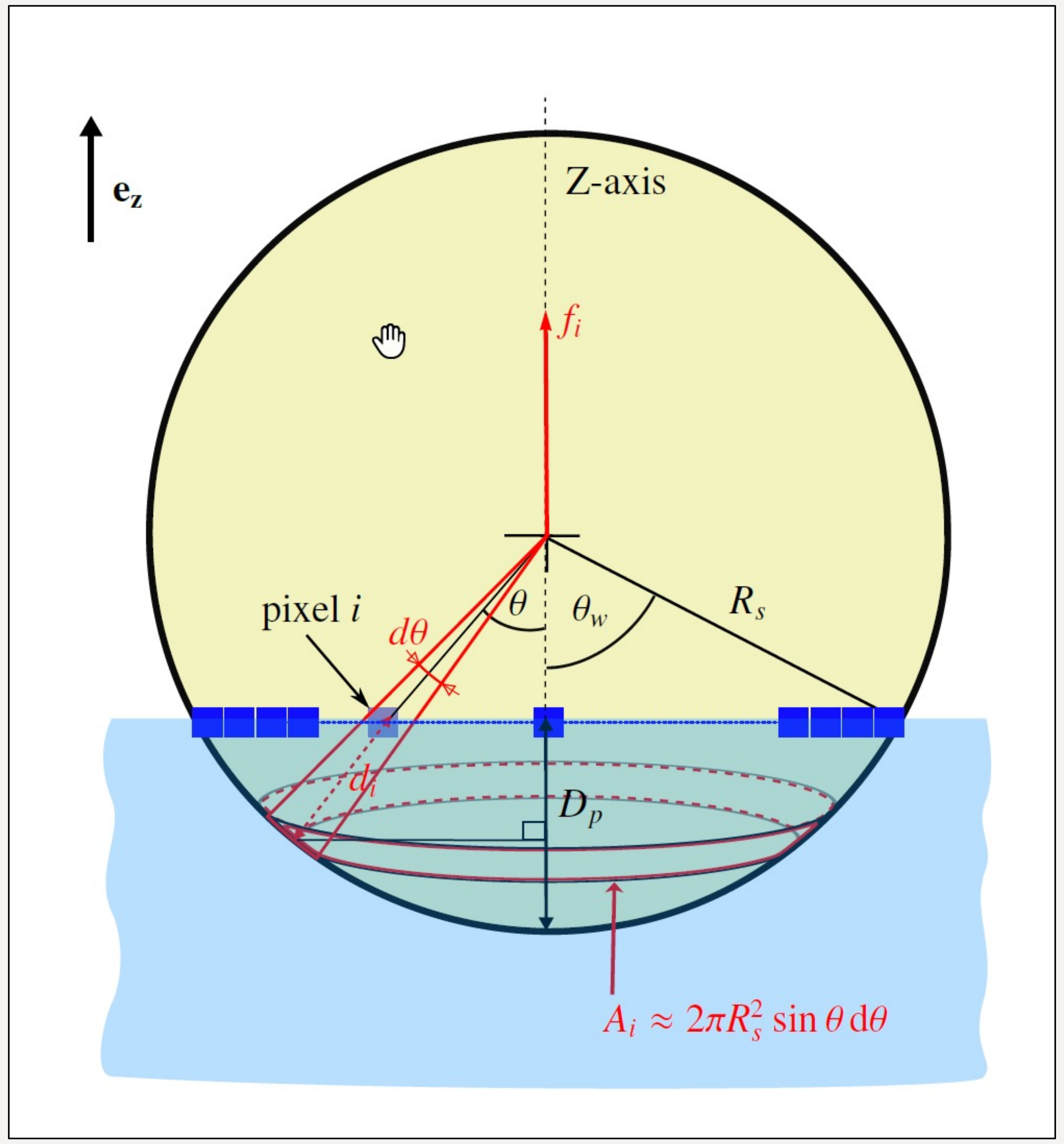


For tracking PDS, the tracking balls must learn how to track local minima better than they do with more simpler structures like granules:

- Training set: establish the true position of the local extrema in each image.
- Training phase: learn the tracking parameters that minimize discrepancies between the final ball positions and the known local extrema
- Cross-validation: assess accuracy in other subfield of data cube.
- Build flow maps by running the process over the whole data cube.



Magnetic Balltracking + ML



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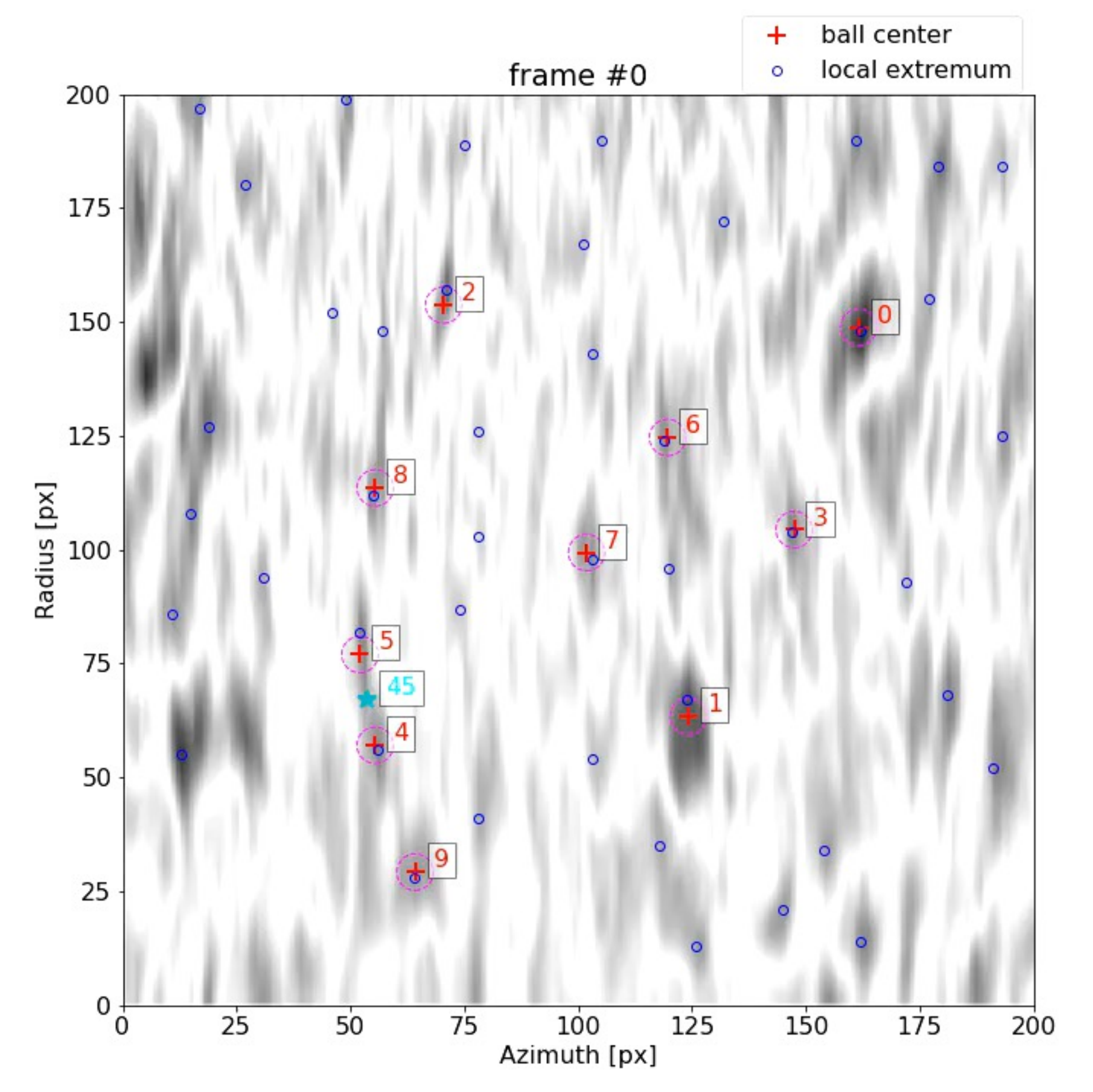


For tracking PDS, the tracking balls must learn how to track local minima better than they do with more simpler structures like photospheric granules:

- Training set: establish true position of local extrema
- Training phase: learn the tracking parameters that minimize discrepancies between ball positions and local extrema
- Cross-validation: assess accuracy in other subfield of data cube.
- Build flow maps by running the process over the whole data cube.

Advantages of the method

- Inherits all advantages of Magnetic Balltracking
- Does not use optical flow approximations
- Robust w.r.t to intensity changes
- Univocal labelling of the tracked features (label <=> ball number) – useful to trace structures back to their origin (solar origin, or formed on the fly, objective of WG 1B)
- Combines well with segmentation techniques for extracting the area of the PDS.
- Highly efficient: equation of motions of the balls are all independent because the balls do not collide, highly parallel.

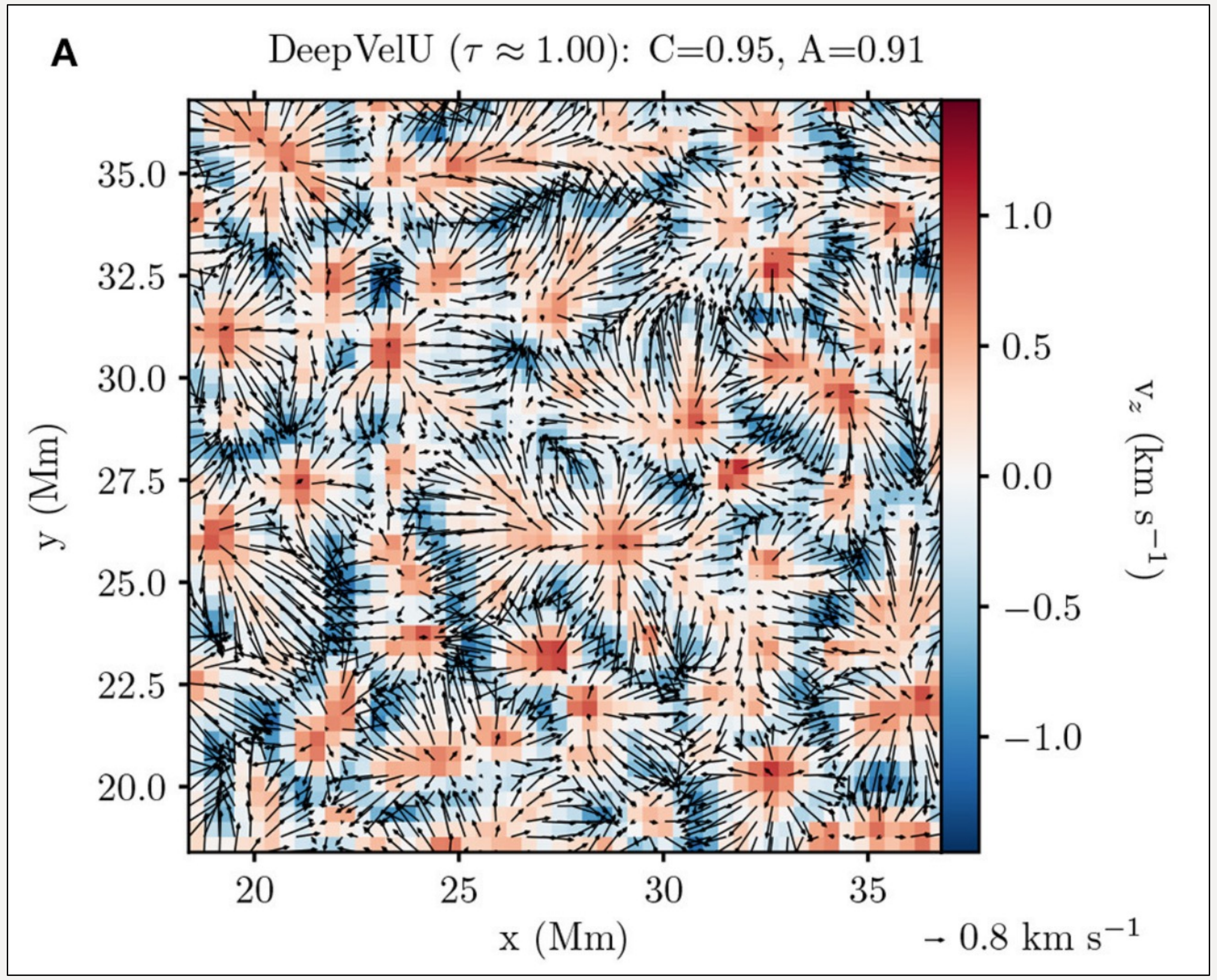
Limits of the method

- Optically thin plasma: ambiguity in the displacements of the local extrema
- Velocity of a given tracking ball may become unrelated to the velocity of the density structure.
- Require additional physical constraints for self-correction (more physics in the cost function, use Kalman filters, exploit the different polarizations from PUNCH)

Deep Learning for tracking plasma flow

Supervised Deep Learning Neural Network:

- MHD simulations to train a Neural Net to infer velocity flows from real observations
- Promising attempts with photospheric flows (*Tremblay & Attie, 2020*).
- Applying a similar architecture on PUNCH data and solar wind simulation is foreseen.



Caveats:

- The NN learns biases of the simulations
- Restrict the discovery space by only reproducing what is known from the training model.
- NNs are poorly explainable, uncertainty of inference on real data difficult to obtain.

However…

- Need a baseline
- Need to find out intrinsic limitations of the NN architecture
- the simpler the simulation, the better

Guidelines for PUNCH data products related to flow tracking

Assess Accuracy of Flow Tracking Methods:

- Each algorithm has its own uncertainties & biases. A result with error bars from an imperfect algorithm is more credible than the perfect result from a perfect algorithm because that one just does not exist.
- Not a competition between methods – need ensemble of methods. Discrepancies between methods => error analysis
- Leverage MHD simulation to get a ground truth and a test set => baseline & sanity checks. e.g. flow tracking challenge from Vadim Uritsky & Valmir Moraes Filho, Aleida Higginson ARMS, Elena Provornikova with GAMERA-Helio simulations.

Heads-up on workflow: ~150 GB / day

- may require efficient larger-than-memory data handling
- Choose libraries and languages wisely for Big Data science
- Document your code with Git!

Communication is key. Remote or hybrid work could become the new normal. Cross-organization discussions should live in a continuum and not just in the narrow time constraints of our workshops and meetings. See NASA's new permanent, cross-organization forum at https://helionauts.org to stay connected with the Heliophysics community. Inside HelioNauts, PUNCH WG leaders are welcome to create their own focused group for more private professional discourse. More than 180 professional heliophysicists joined. You can share and advertize your papers with a much greater impact and persistent visibility than you would ever have on Facebook or Slack. This platform will eventually be advertized in SolarNews.