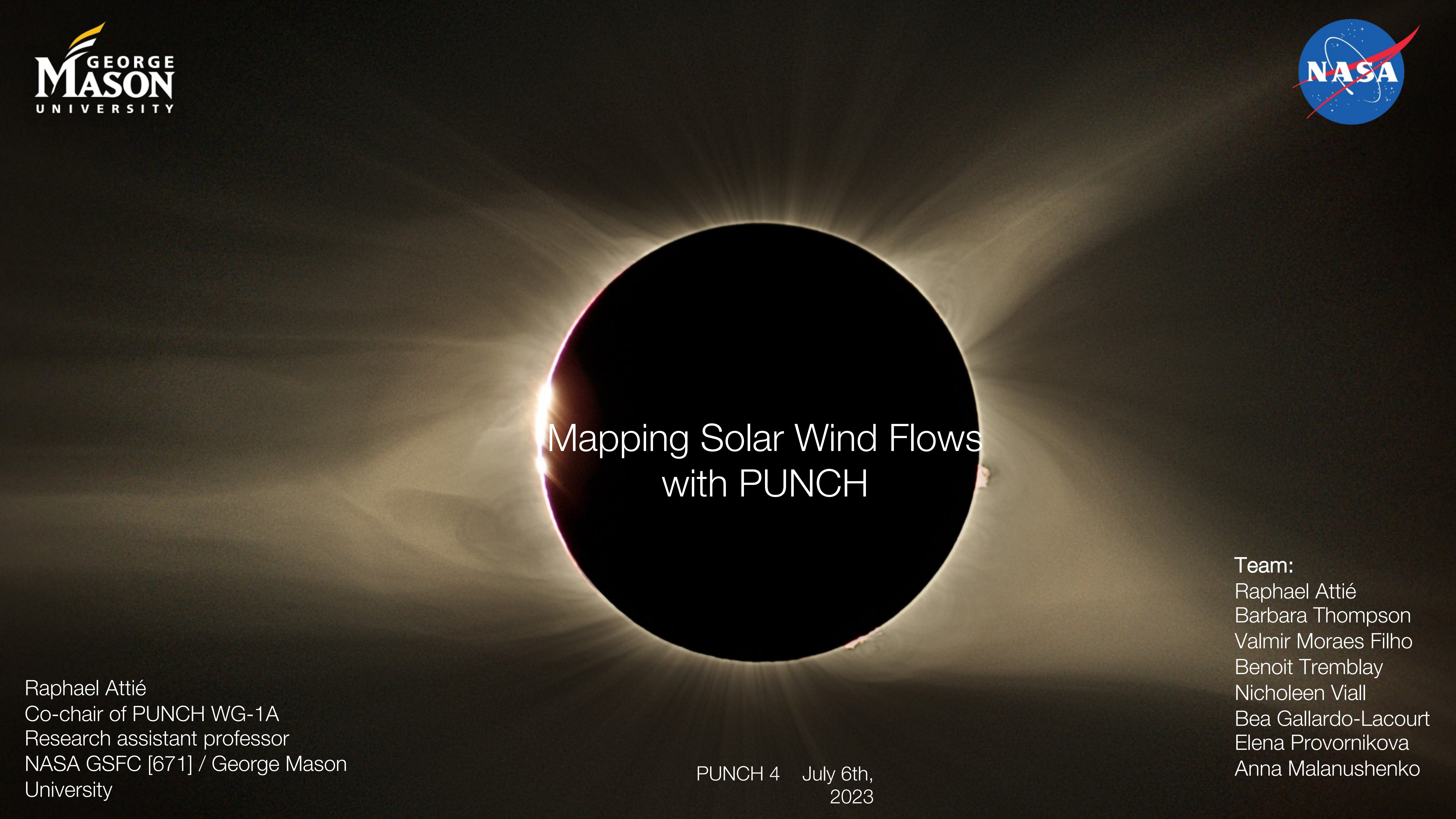


Mapping Solar Wind Flows with PUNCH

Raphael Attié
Co-chair of PUNCH WG-1A
Research assistant professor
NASA GSFC [671] / George Mason University

PUNCH 4 July 6th, 2023

Team:
Raphael Attié
Barbara Thompson
Valmir Moraes Filho
Benoit Tremblay
Nicholeen Viall
Bea Gallardo-Lacourt
Elena Provornikova
Anna Malanushenko

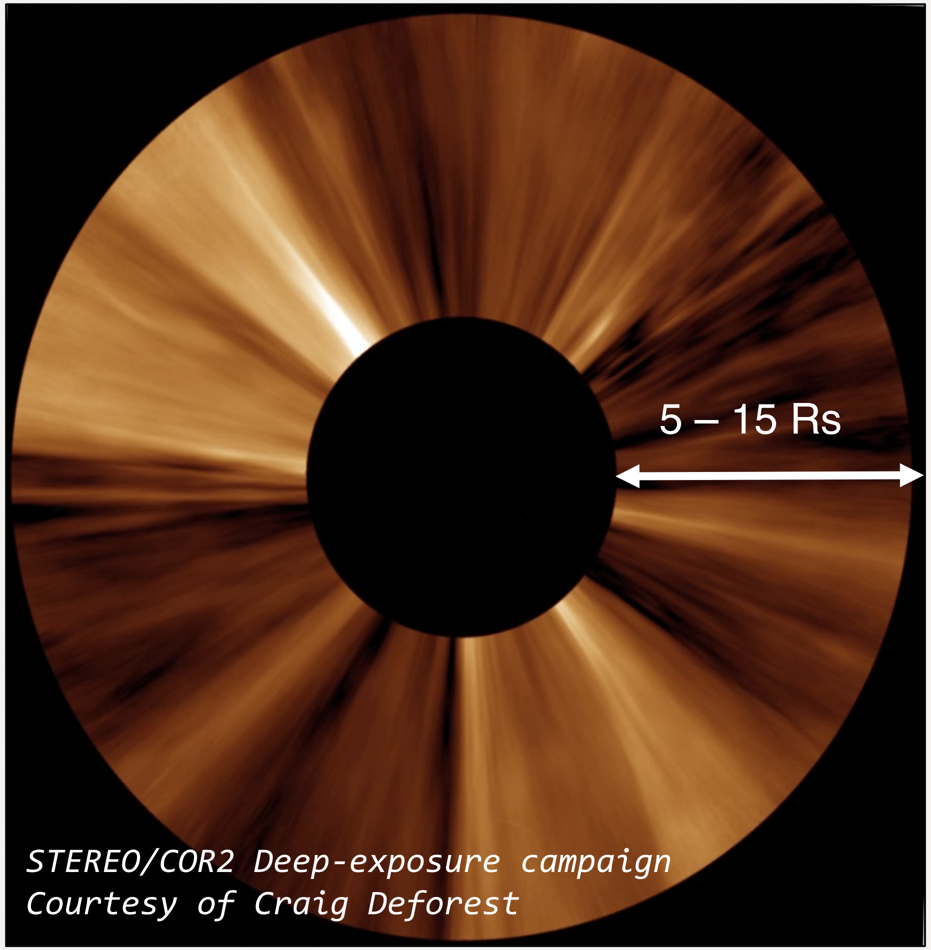
MAPPING SOLAR WIND FLOWS: **WHY?**

- Understand the interplay between the corona and planetary environments

- By expanding as the SW flows outward, relatively small changes near the sun’s surface feed planet-wide space weather effects. Measuring that flow is necessary to relate the dynamics in the environment of Earth and the other planets to what has happened upstream.

- Critical lack of flow maps in the solar wind, addressed by delivering solar wind flow fields with quantifiable uncertainties

MAPPING SOLAR WIND FLOWS: **HOW?**



HOW DO WE TRACK PLASMA FLOWS?

- Optical flow
- Physics-based
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

Definition (qualitative): quantify the motion of brightness patterns across a time series of images in a sparse or dense flow field.

- Physics-based

- Neural Networks

- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

Definition (qualitative): quantify the motion of brightness patterns across a time series of images in a sparse or dense flow field.

Methods:
- **Differential**
- **Feature matching**
- **Frequency based**

- Physics-based
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

○ Optical flow

Methods:
- **Differential**
- Feature matching
- Frequency based

Definition (qualitative): quantify the motion of brightness patterns across a time series of images in a sparse or dense flow field.

$$\partial_x I u + \partial_y I v + \partial_t I = 0$$

I(x,y,t): Brightness (Image intensity)
(u,v): (x,y)-component of the 2D velocity vector in the image plane

○ Physics-based

○ Neural Networks

○ Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- **Optical flow**

  Methods:
  - **Differential**
  - Feature matching
  - Frequency based

- Physics-based

- Neural Networks

- Ball-tracking

Definition (qualitative): quantify the motion of brightness patterns across a time series of images in a sparse or dense flow field.

$$\partial_x I u + \partial_y I v + \partial_t I = 0$$

$I(x,y,t)$: Brightness (Image intensity)
(u,v): (x,y)-component of the 2D velocity vector in the image plane

- 1 optical flow equation
- 2 unknowns (u,v)
- In reality: noise => optical flow equation => error term

⇒ Need additional constraints: e.g. smoothness constraints (no sharp transitions)
⇒ Minimization problem

Horn & Schunk (1981)

$$\begin{aligned} \epsilon_b &= \partial_x I u + \partial_y I v + I_t \\ \epsilon_s &= \partial_x u^2 + \partial_y u^2 + \partial_x v^2 + \partial_y v^2 \end{aligned}$$

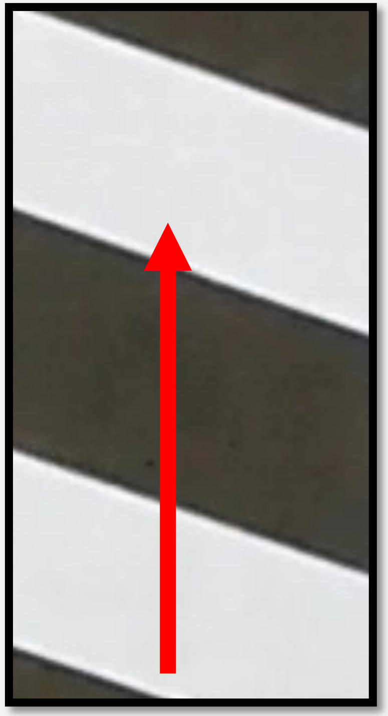
HOW DO WE TRACK PLASMA FLOWS?

○ Optical flow

Methods:
- **Differential**
- **Feature matching**
- **Frequency based**

$$\partial_x I u + \partial_y I v + \partial_t I = 0$$

Caveat



Apparent motion: upward ↑

○ Physics-based

○ Neural Networks

○ Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

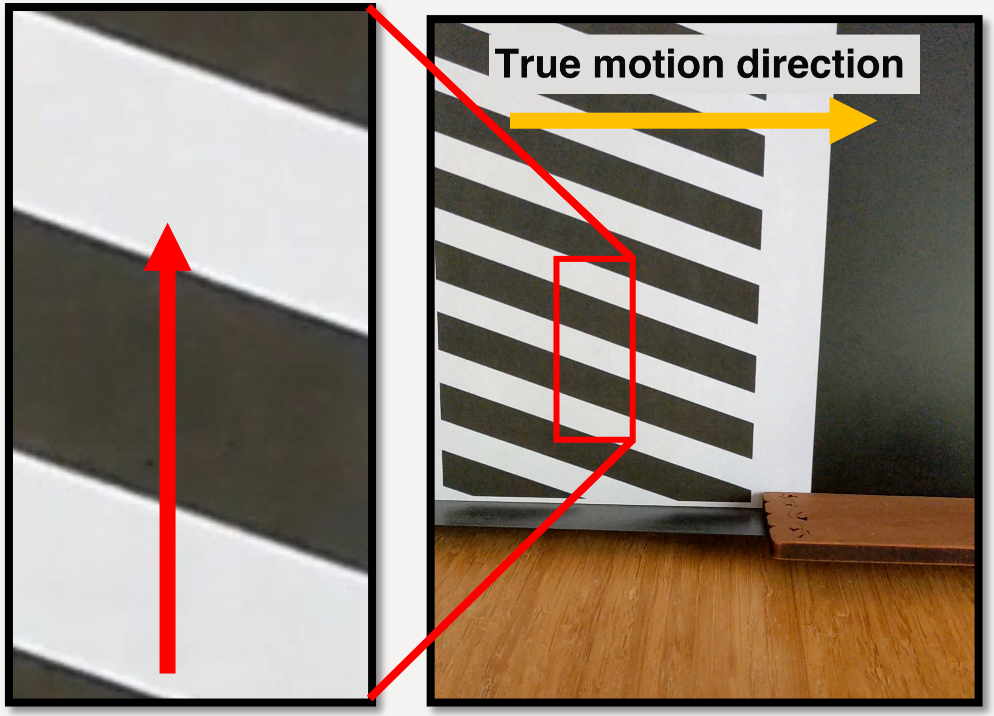
○ Optical flow

Methods:

- **Differential**
- Feature matching
- Frequency based

$$\partial_x I u + \partial_y I v + \partial_t I = 0$$

Caveat



Apparent motion: upward ↑

True motion: purely horizontal left to right

○ Physics-based

○ Neural Networks

○ Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

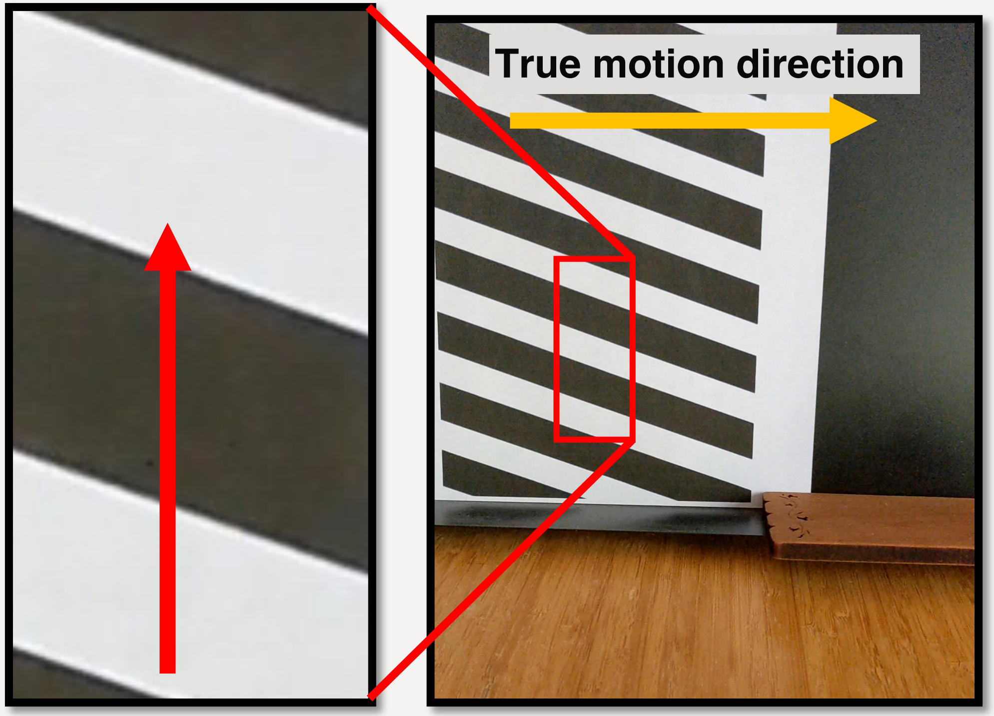
Methods:
- **Differential**
- **Feature matching**
- **Frequency based**

$$\partial_x I u + \partial_y I v + \partial_t I = 0$$

Caveat

When the image has locally no gradient in either or both direction, the motion vector cannot be determined

➢ **Aperture problem**



Apparent motion: upward ↑

True motion: purely horizontal left to right

- Physics-based
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

Methods:
- **Differential**
- Feature matching
- Frequency based

- Physics-based
- Neural Networks
- Ball-tracking

$$\partial_x I u + \partial_y I v + \partial_t I = 0$$

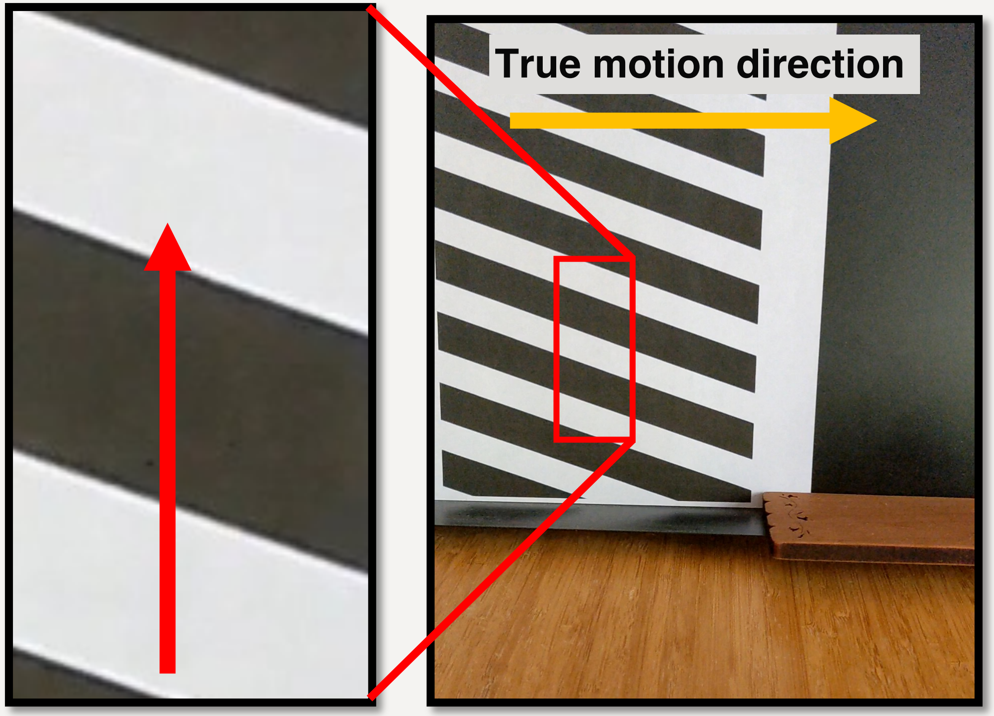
Caveat

When the image has locally no gradient in either or both direction, the motion vector cannot be determined

➢ **Aperture problem**

Some implementations can circumvent this problem:
- ✓ Numerical schemes fill in the gap
- ✓ Hierarchical/pyramidal processing

But… not tested yet for PUNCH



Apparent motion: upward ↑

True motion: purely horizontal left to right

HOW DO WE TRACK PLASMA FLOWS?

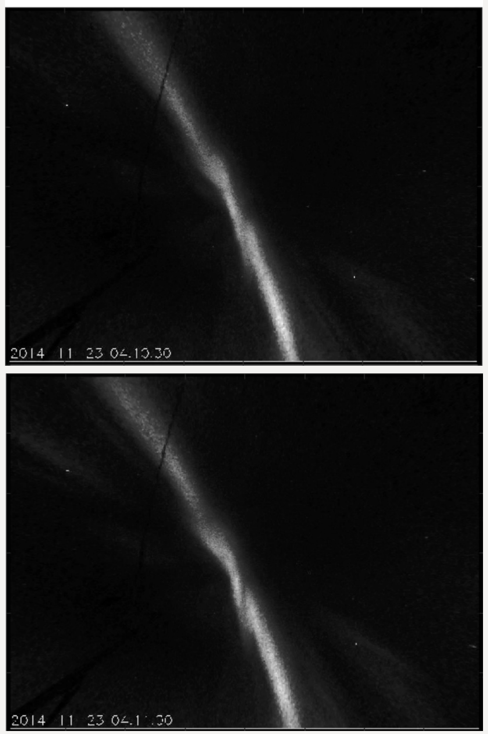
- ## Optical flow

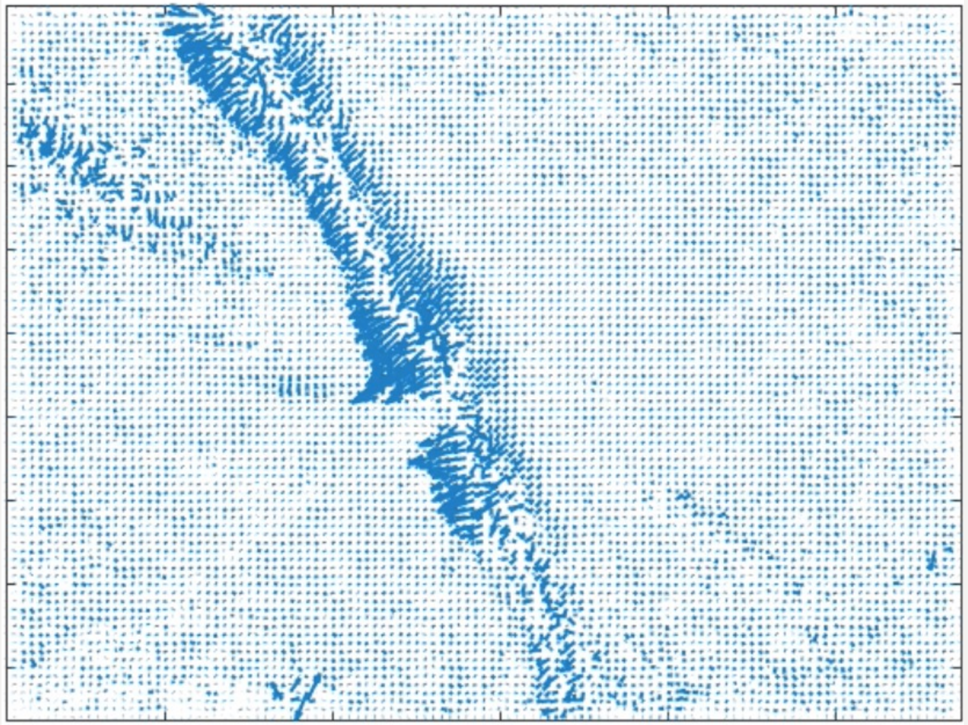
Methods:

- **Differential**
- Feature matching
- Frequency based

Application of differential method by **Bea Gallardo-Lacourt** for tracking auroras:

Dense optical flow





- ## Physics-based

- ## Neural Networks

- ## Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

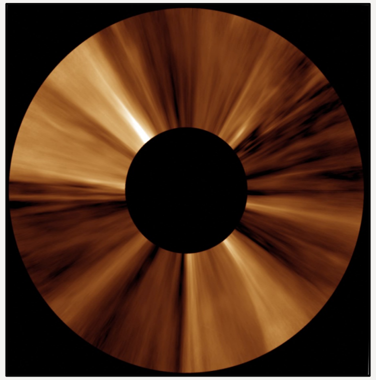
Methods:
- **Differential**
- Feature matching
- Frequency based

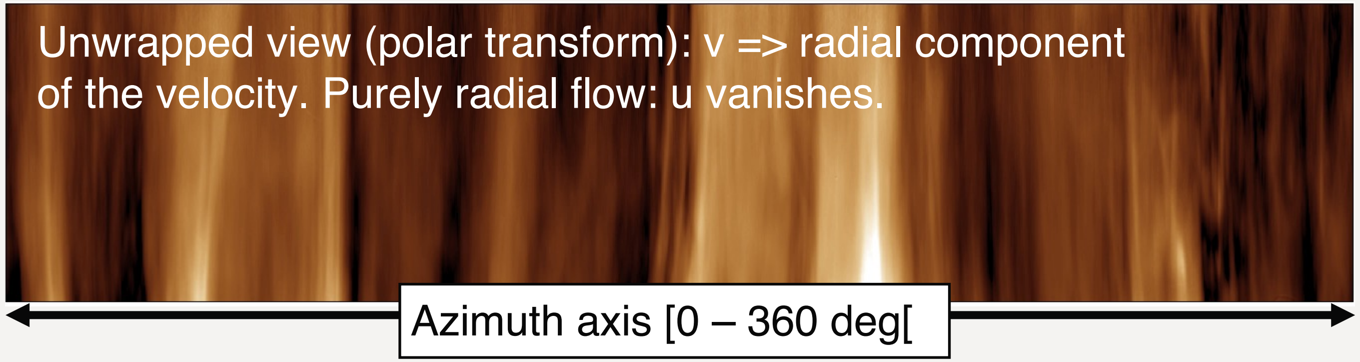
- Physics-based
- Neural Networks
- Ball-tracking

$$\partial_x I u + \partial_y I v + \partial_t I = 0$$

- 1 optical flow equation
- 2 unknowns (u,v)

$\Rightarrow$ Need additional constraints





HOW DO WE TRACK PLASMA FLOWS?

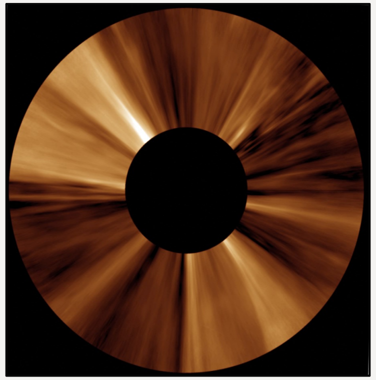
- Optical flow

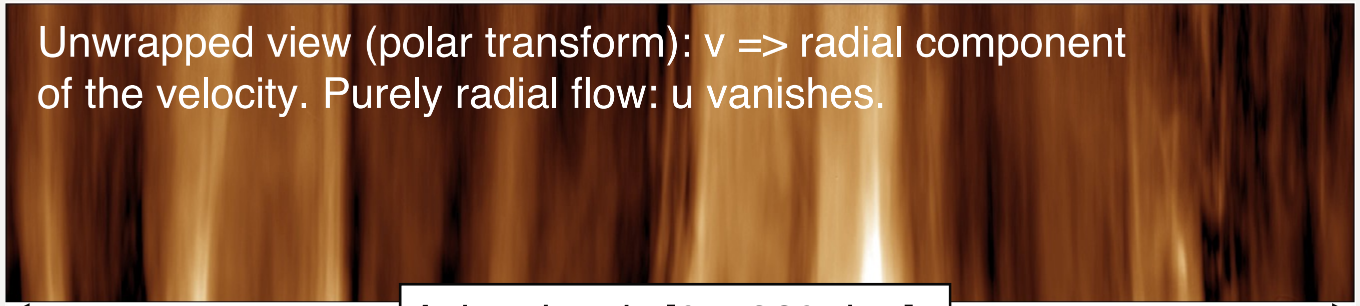
  Methods:
  - **Differential**
  - Feature matching
  - Frequency based

$$\cancel{\partial_x I} u + \partial_y I v + \partial_t I = 0$$

- 1 optical flow equation
- 2 unknowns (u,v)

$\Rightarrow$ Need additional constraints





Azimuth axis [0 – 360 deg[

- Physics-based
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- **Optical flow**

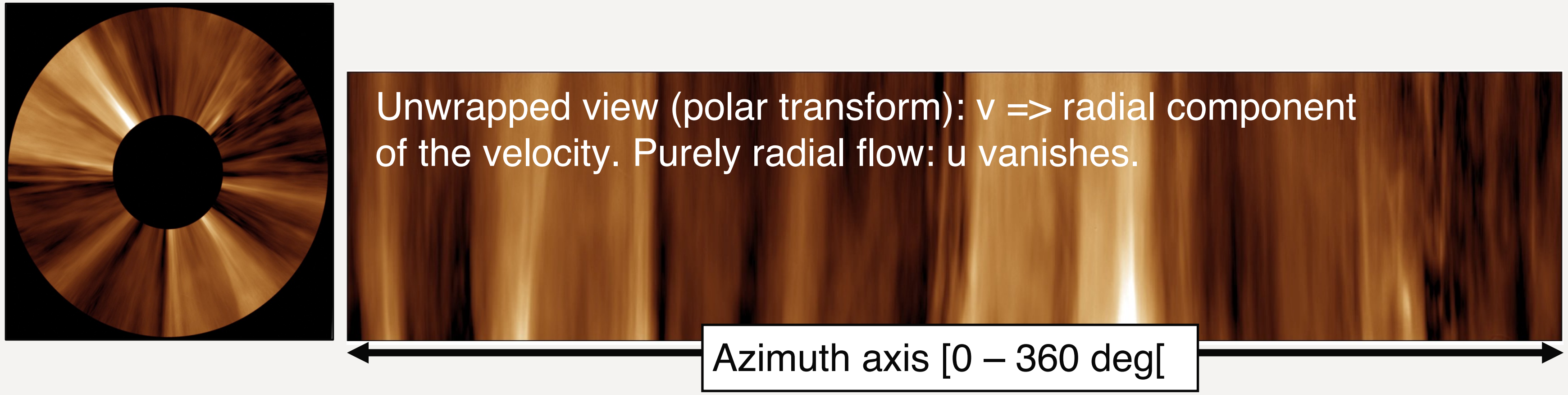
  Methods:
  - **Differential**
  - Feature matching
  - Frequency based

- Physics-based
- Neural Networks
- Ball-tracking

$$\cancel{\partial_x I u} + \partial_y I v + \partial_t I = 0$$

- 1 optical flow equation
- 2 unknowns (u,v)

$\Rightarrow$ Need additional constraints



=> Differential methods are worth a shot

HOW DO WE TRACK PLASMA FLOWS?

○ Optical flow

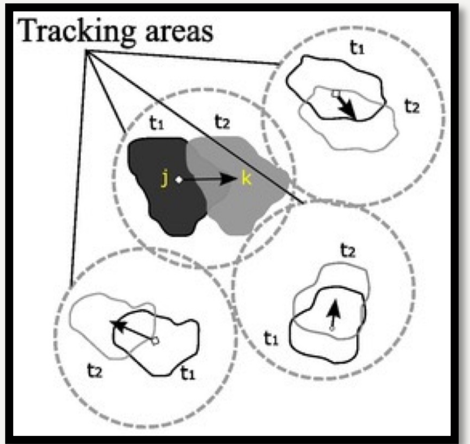
Methods:

- Differential
- **Feature matching**
- Frequency based

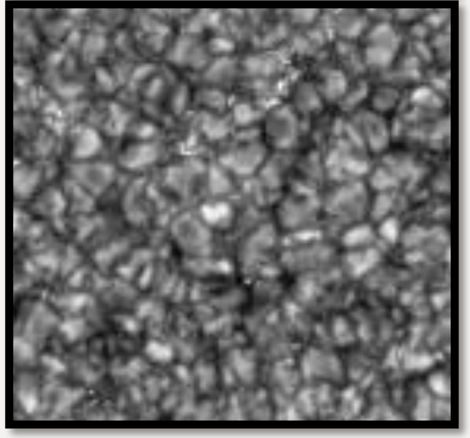
Metric of similarity: correlation

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

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



Local Correlation tracking: optical flow based on “correlation” similarity metric, telling how much two tracking areas in consecutive images are similar. The position of maximum correlation yields the local motion vector.



○ Physics-based

○ Neural Networks

○ Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

Methods:
- Differential
- Feature matching
- **Frequency based**

Initial brightness

$$I(\mathbf{x}, t) = I_0(\mathbf{x})\delta(\mathbf{x} - \mathbf{v}t)$$

- Physics-based
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

Methods:
- Differential
- Feature matching
- **Frequency based**

Initial brightness

$$I(\mathbf{x},t) = I_0(\mathbf{x})\delta(\mathbf{x} - \mathbf{v}t)$$

$$\hat{I}(\mathbf{k},\omega) = \hat{I}_0(\mathbf{k},\omega)\delta(\mathbf{k}\cdot\mathbf{v} + \omega)$$

- Physics-based
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

Methods:
- Differential
- Feature matching
- **Frequency based**

Initial brightness

$$I(\mathbf{x}, t) = I_0(\mathbf{x})\delta(\mathbf{x} - \mathbf{v}t)$$

$$\hat{I}(\mathbf{k}, \omega) = \hat{I}_0(\mathbf{k}, \omega)\delta(\mathbf{k} \cdot \mathbf{v} + \omega)$$

$$\rightarrow \mathbf{k} \cdot \mathbf{v} + \omega = 0$$ **Optical flow equation**

- Physics-based
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

  Methods:
  - Differential
  - Feature matching
  - **Frequency based**

- Physics-based

- Neural Networks

- Ball-tracking

Initial brightness

$$I(\mathbf{x}, t) = I_0(\mathbf{x})\delta(\mathbf{x} - \mathbf{v}t)$$

$$\hat{I}(\mathbf{k}, \omega) = \hat{I}_0(\mathbf{k}, \omega)\delta(\mathbf{k} \cdot \mathbf{v} + \omega)$$

$$\rightarrow \mathbf{k} \cdot \mathbf{v} + \omega = 0$$ **Optical flow equation**

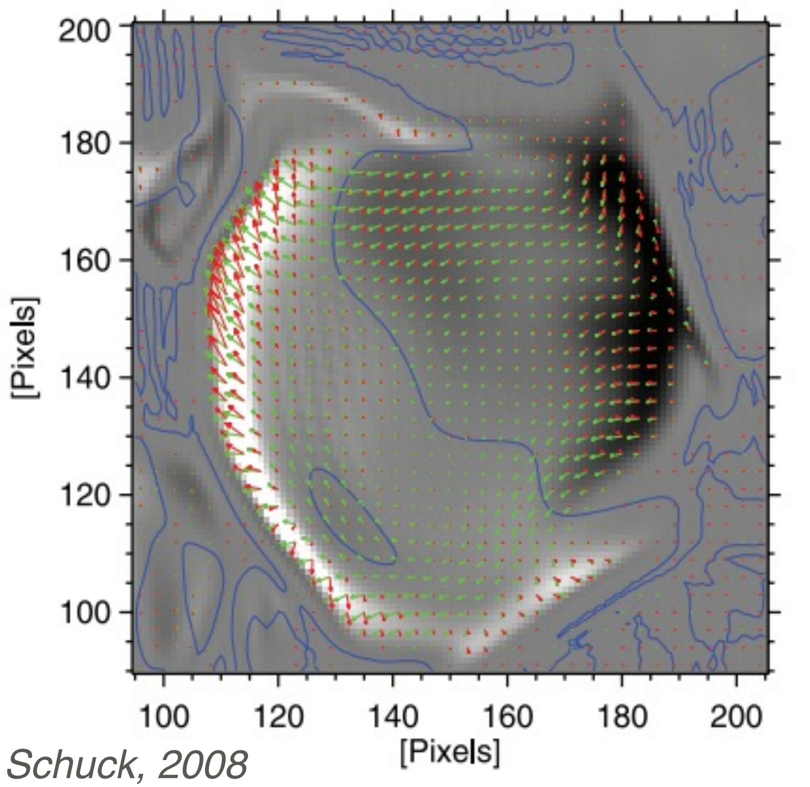
- No practical implementation in place for heliospheric imagery
- Makes sense for tracking **<u>periodic</u>** density structures

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow
- Physics-based
- Neural Networks
- Ball-tracking

➢ **Affine velocity estimators:**
DAVE & DAVE4VM (Schuck, 2006, 2008)
Using magnetic field measurements, account for magnetic induction equation to track the velocity of magnetic footpoints in the photosphere.

➢ More accurate results than correlation-based methods



Schuck, 2008

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow
- Physics-based
  - **PUNCH:** polarized brightness
  - **Physics:** Thompson scattering
  - **Optical flow:** additional physical constraints should be investigated to minimize the uncertainty when relying solely on the displacements of brightness patterns.
- Neural Networks
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow

Supervised Neural Nets are trained with [MHD] simulations, where a network is presented input observations (synthetic granulation) and an output ground truth (flow field), and the neural net creates a mapping functions between the input and output.

- Physics-based

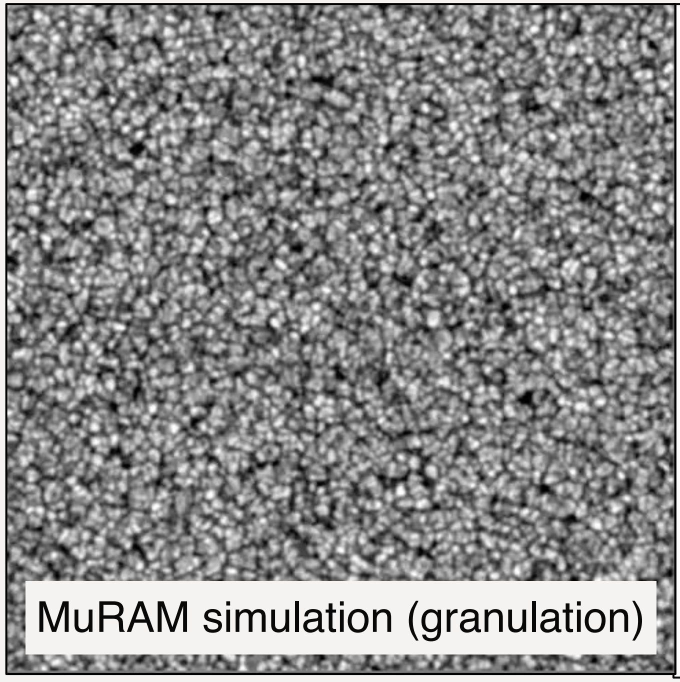
- Neural Networks
  - CNN: supervised
  - PiNNs: unsupervised

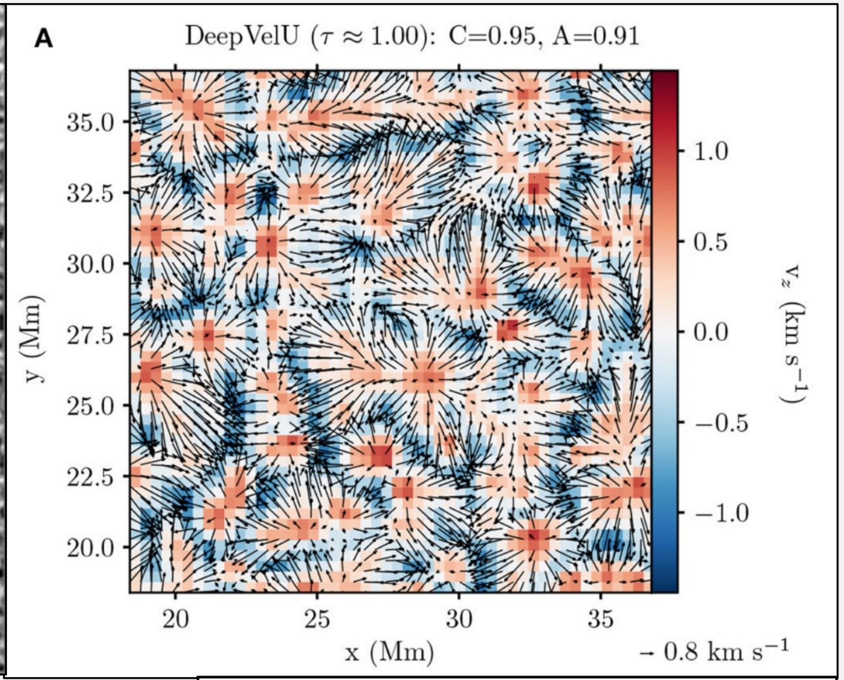
- Ball-tracking

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow
- Physics-based
- Neural Networks
  - CNN: supervised
  - PiNNs: unsupervised
- Ball-tracking

Supervised Neural Nets are trained with [MHD] simulations, where a network is presented input observations (synthetic granulation) and an output ground truth (flow field), and the neural net creates a mapping functions between the input and output.



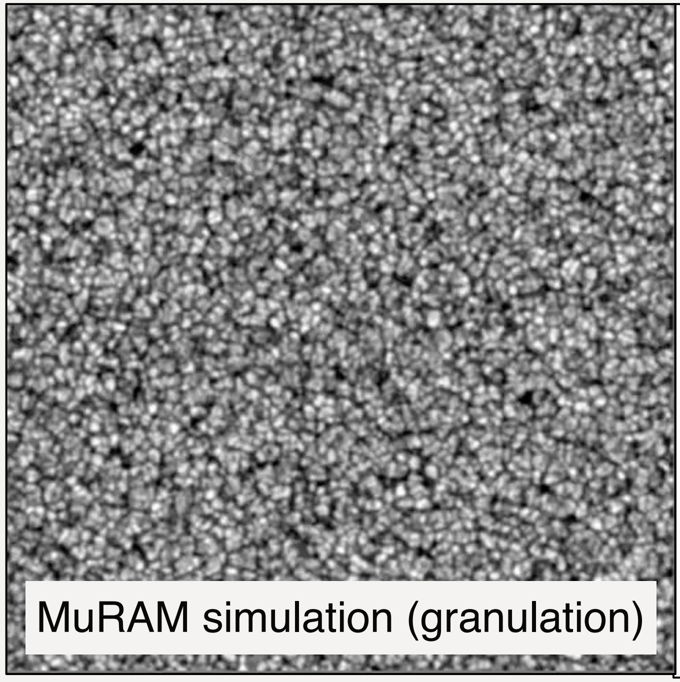


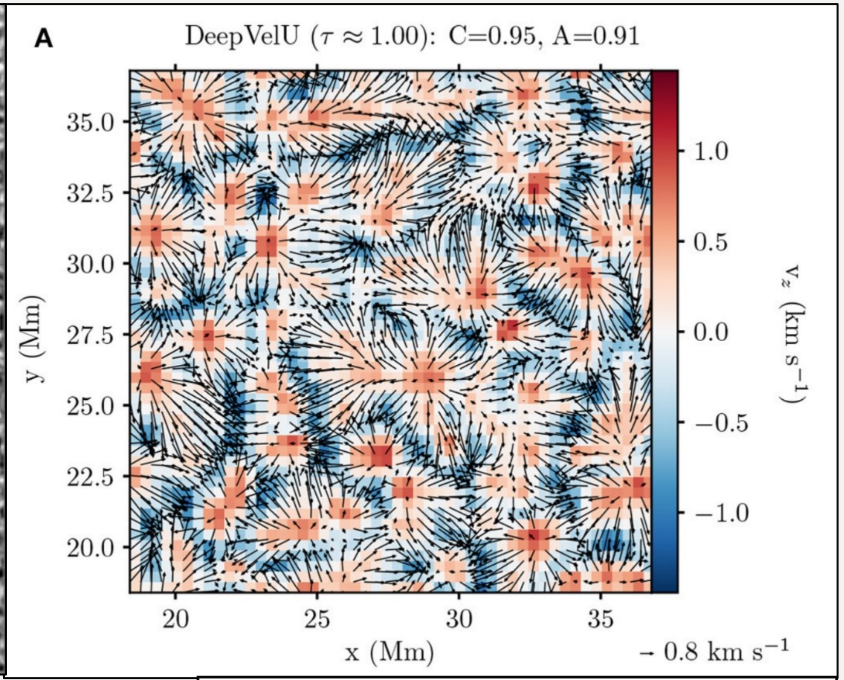
Photospheric flow derived from supervised "U-Net" by Tremblay & Attie (2020)

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow
- Physics-based
- Neural Networks
  - CNN: supervised
  - PiNNs: unsupervised
- Ball-tracking

Supervised Neural Nets are trained with [MHD] simulations, where a network is presented input observations (synthetic granulation) and an output ground truth (flow field), and the neural net creates a mapping functions between the input and output.





Photospheric flow derived from supervised "U-Net" by Tremblay & Attie (2020)

Caveat: may not generalize well enough if systematics, or the lack of simulated physics make the real observations and simulations deviate from each other.

HOW DO WE TRACK PLASMA FLOWS?

- Optical flow
- Physics-based
- Neural Networks
  - CNN: supervised
  - PiNNs: unsupervised
- Ball-tracking

PiNNs are Unsupervised Physics-informed Neural Nets: The forward propagation is using observations as input, but instead of a ground truth flow field at the output, the forward/backprop minimization is driven by physics equations that describe the mechanisms that **we believe** are at play.

Advantages:

- Efficient PDE solvers that can learn non-linear relationships

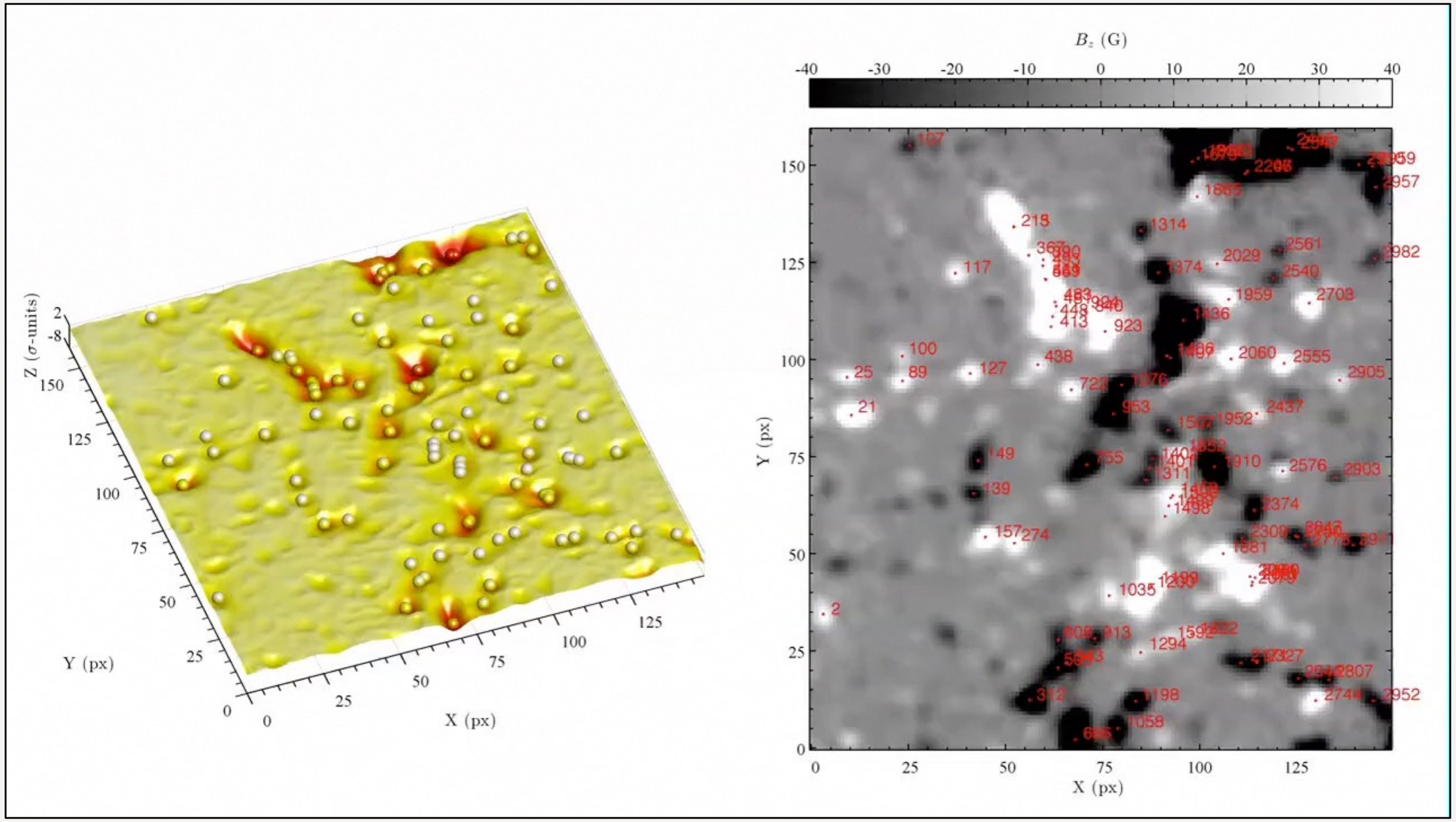
Disadvantages:

- Carry the uncertainty on to what extent the physics equations describe the observations, which is a human-based choice, restrict discovery space

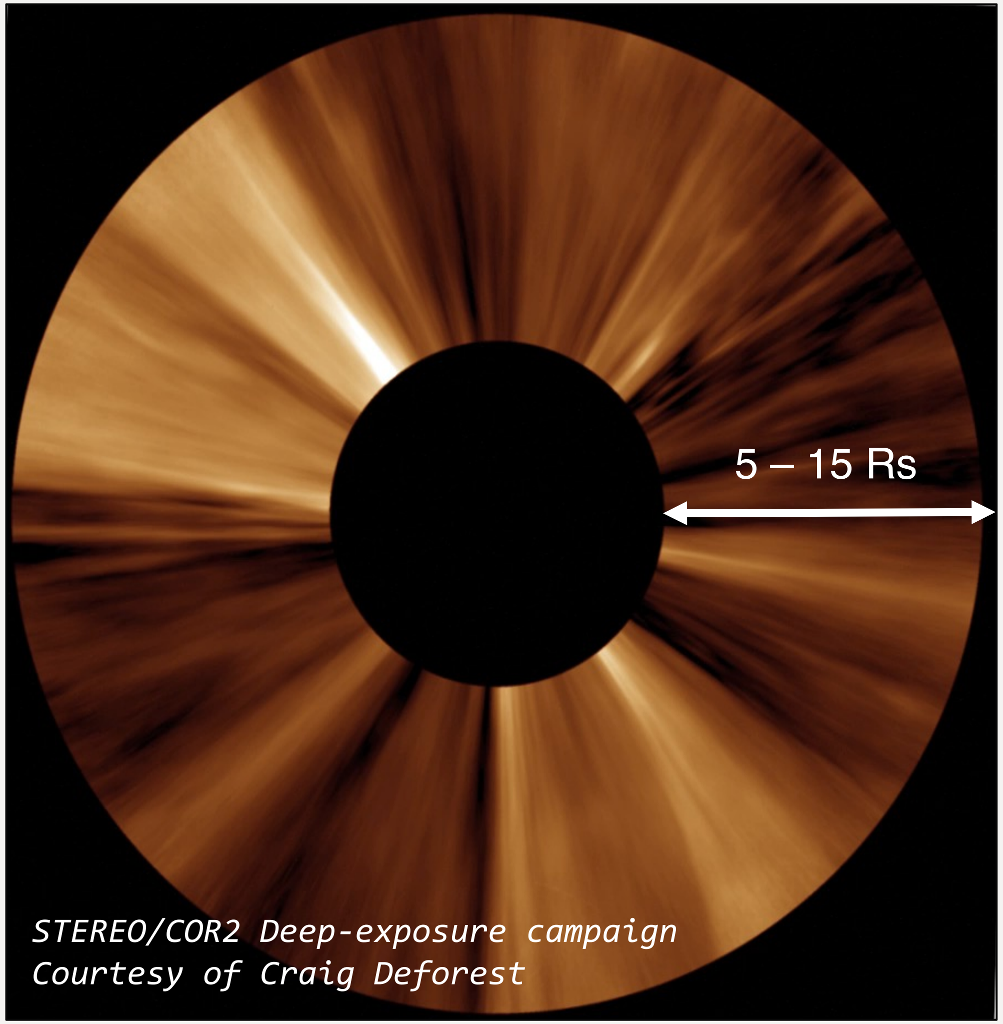
HOW DO WE TRACK PLASMA FLOWS?

- Optical flow
- Physics-based
- Neural Networks
- Ball-tracking

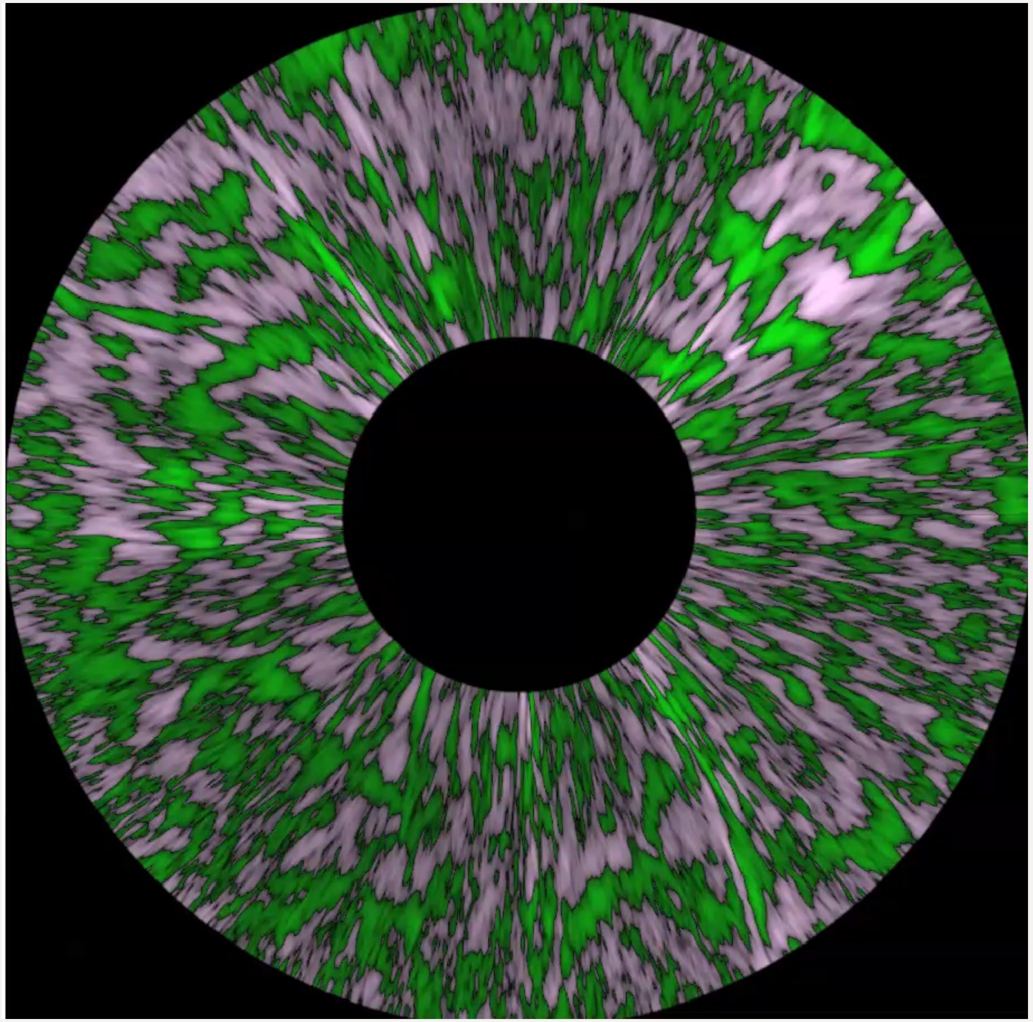
Magnetic Balltracking (*Attie & Innes, 2015*): Tracking in the **Lagrange** reference frame of moving magnetic features.
Output a “sparse” flow field, motion vectors for a set of moving objects (here, magnetic moving fragments in magnetograms), and feature characteristics (lifetimes, sizes, etc…)



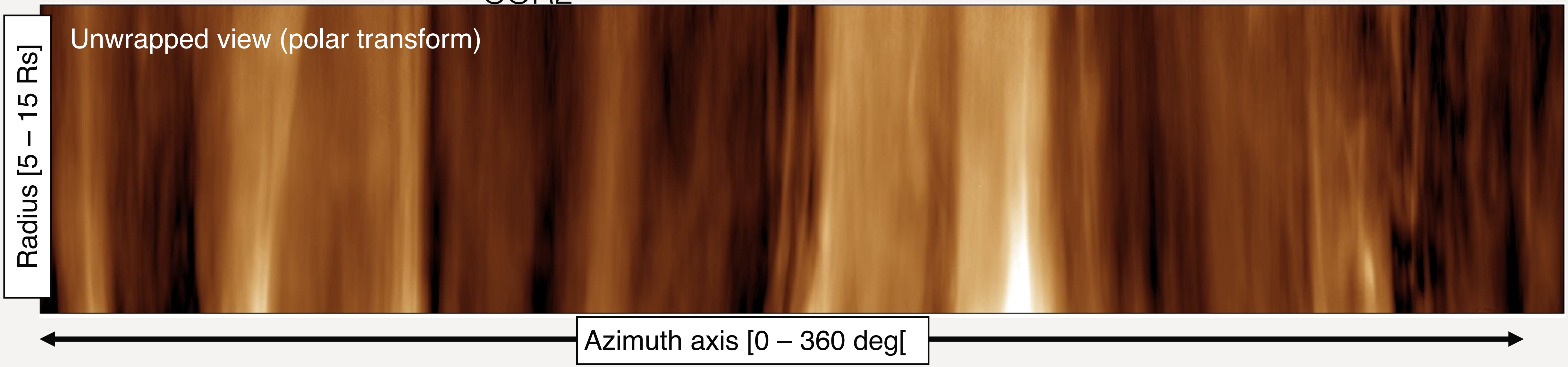
BALLTRACKING APPLIED TO STEREO/COR2

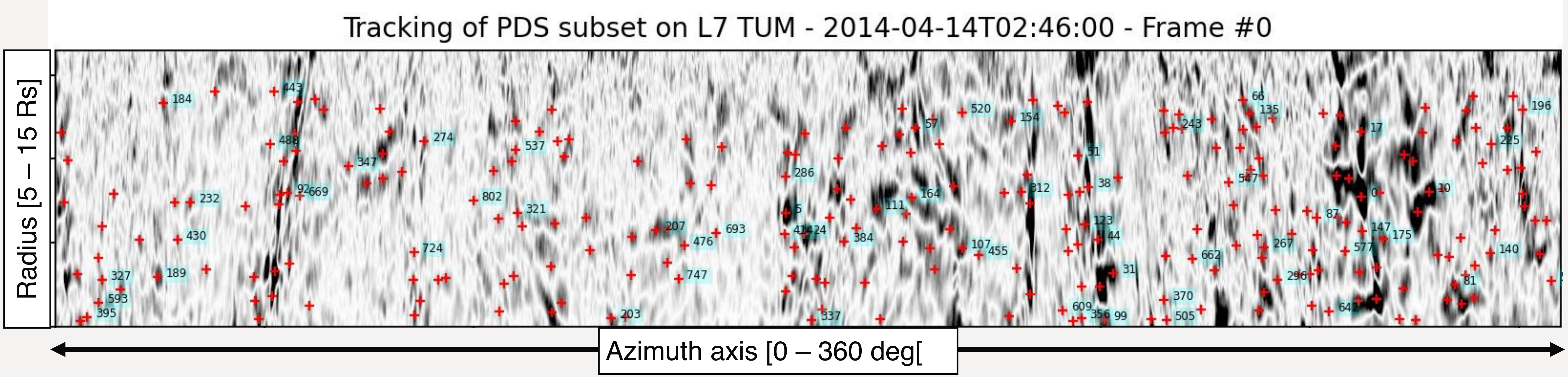


Temporal-unsharp masked (by Craig Deforest)



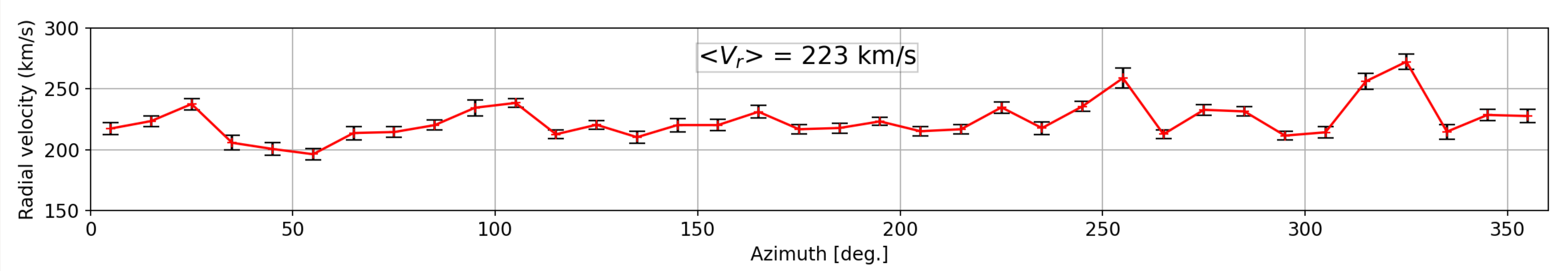
BALLTRACKING APPLIED TO STEREO COR2

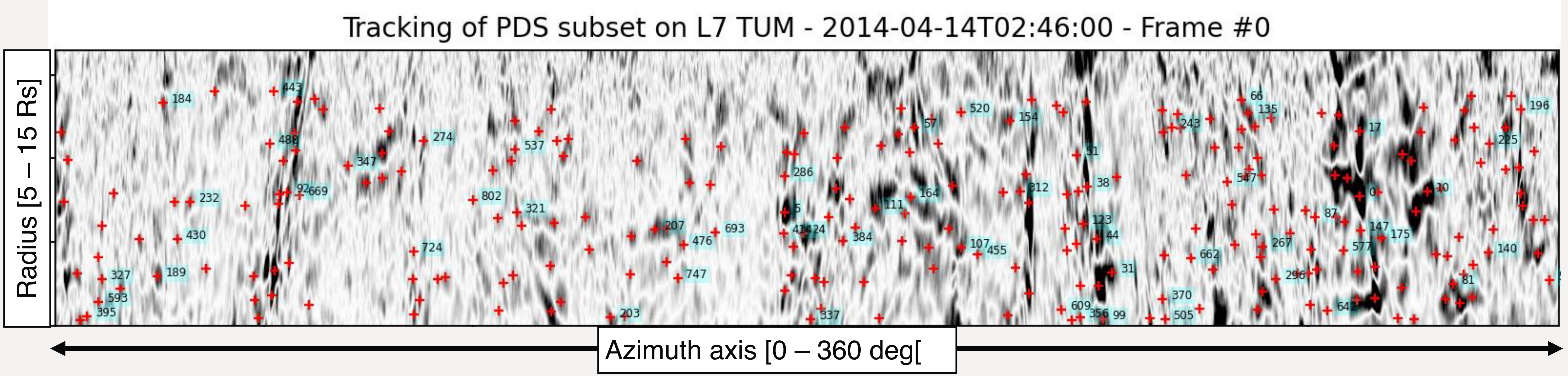




Magnetic Balltracking applied to plasma density structures in the solar wind

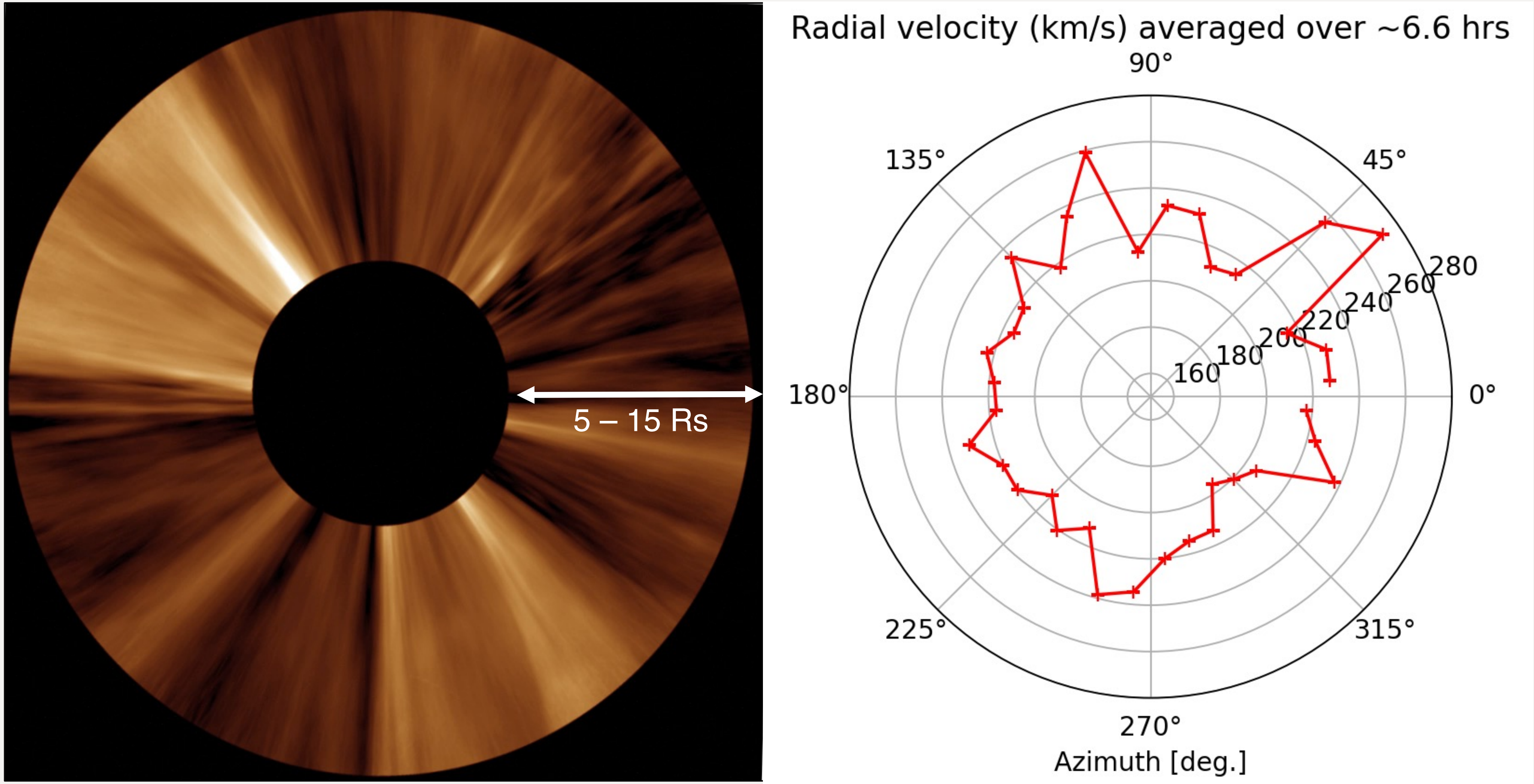
BALLTRACKING APPLIED TO STEREO/COR2



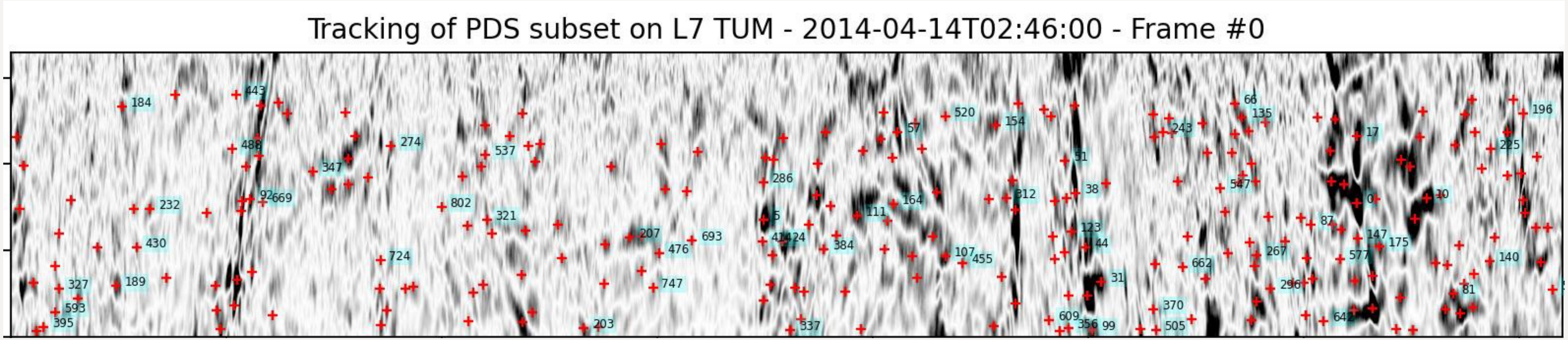


Magnetic Balltracking applied to plasma density structures in the solar wind

BALLTRACKING APPLIED TO STEREO/COR2

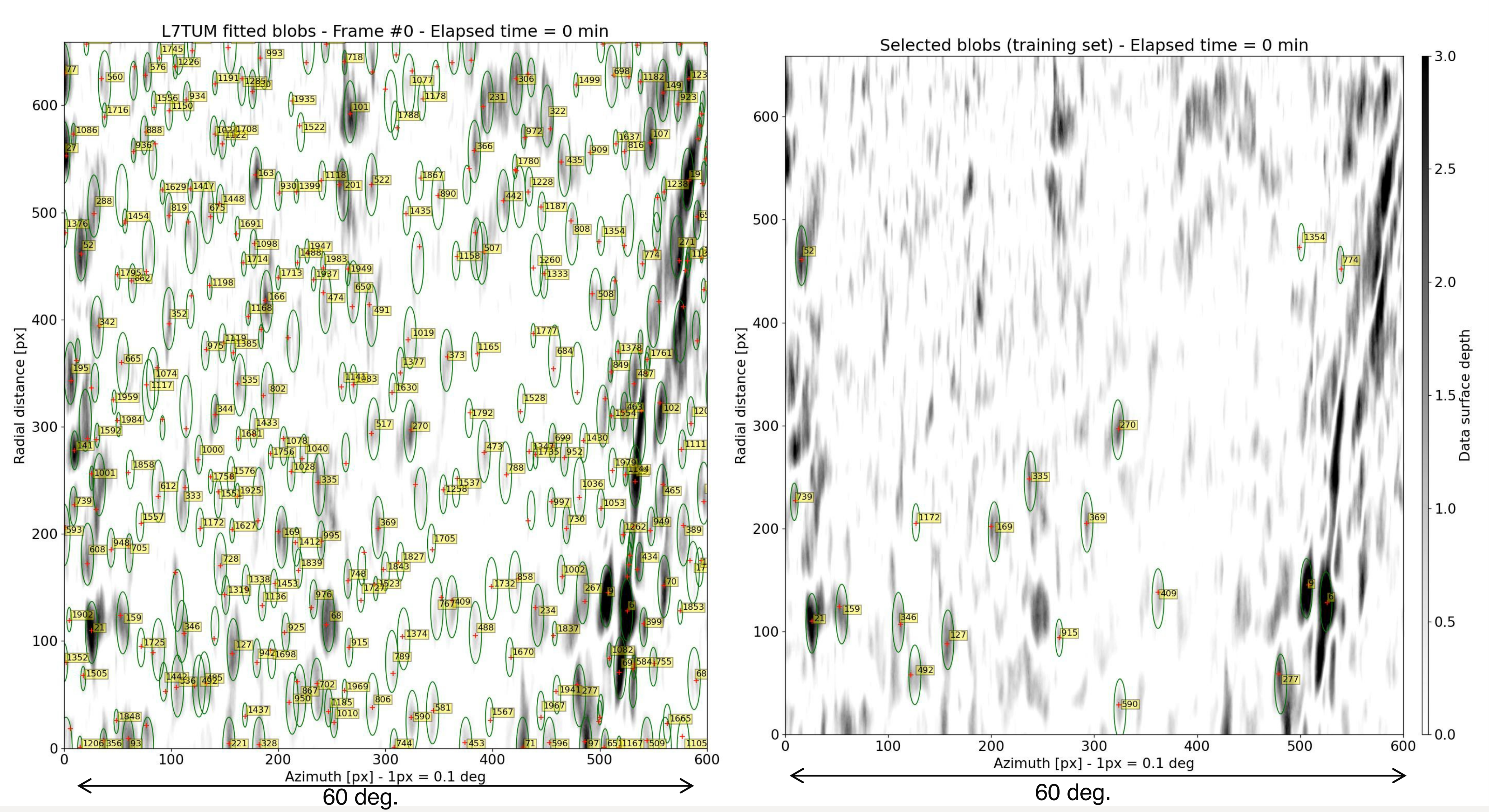


BALLTRACKING APPLIED TO STEREO/COR2



Caveats: taken as-is, flow field still subject to 3D location uncertainty (optically thin plasma, projection effects, etc…)

Training sets: manually tracked and ellipse-fitted density structures used to fine-tune Magnetic Balltracking



Training sets:

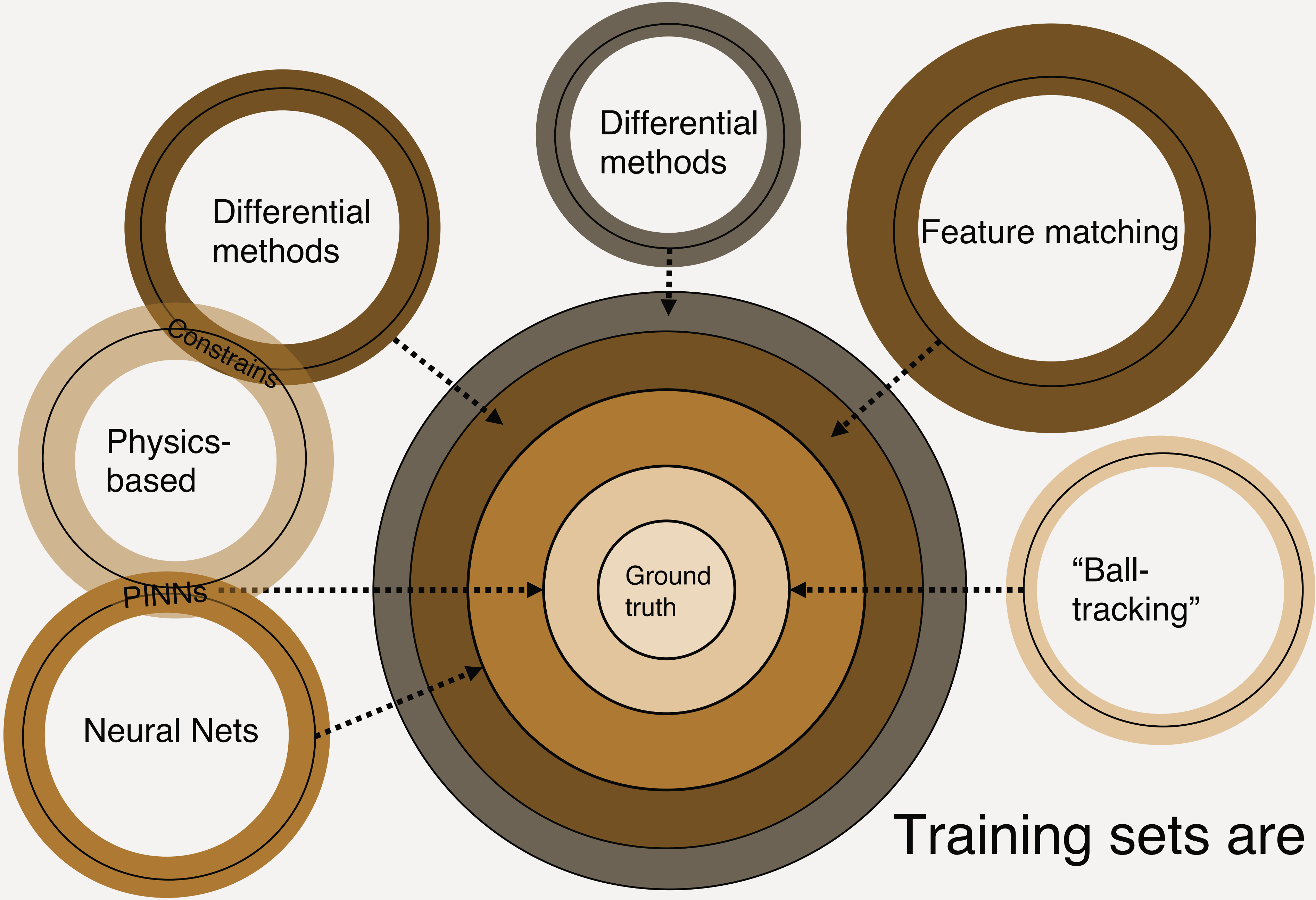
- ✓ **Must provide density & velocity flows used as “ground truth”**
- ✓ **Necessary to tune algorithms, evaluate performance & uncertainties**
- ✓ **Statistically significant for separating Training/Validating/Testing to overcome overfitting**

- ▪ **Available**: Manually tracked density structures with quantified uncertainties from STEREO COR2
- ▪ **Available**: Synthetic datasets from Valmir Moraes Filho (SynCOM, See talk)

- o **Planned**: MHD simulations: jets / jetlets (*Wyper et al. 2022, ApJL 941 L29*)
- o **Planned**: GAMERA / CMEs (see talks from Anna Malanushenko and Elena Provornikova)

- ➢ input to pipeline for PUNCH-like observations (See Sarah Gibson talk)

CONCLUSIO
N



Training sets are #1 priority