Trajectory-based Flow Feature Tracking in Joint Particle/Volume Datasets

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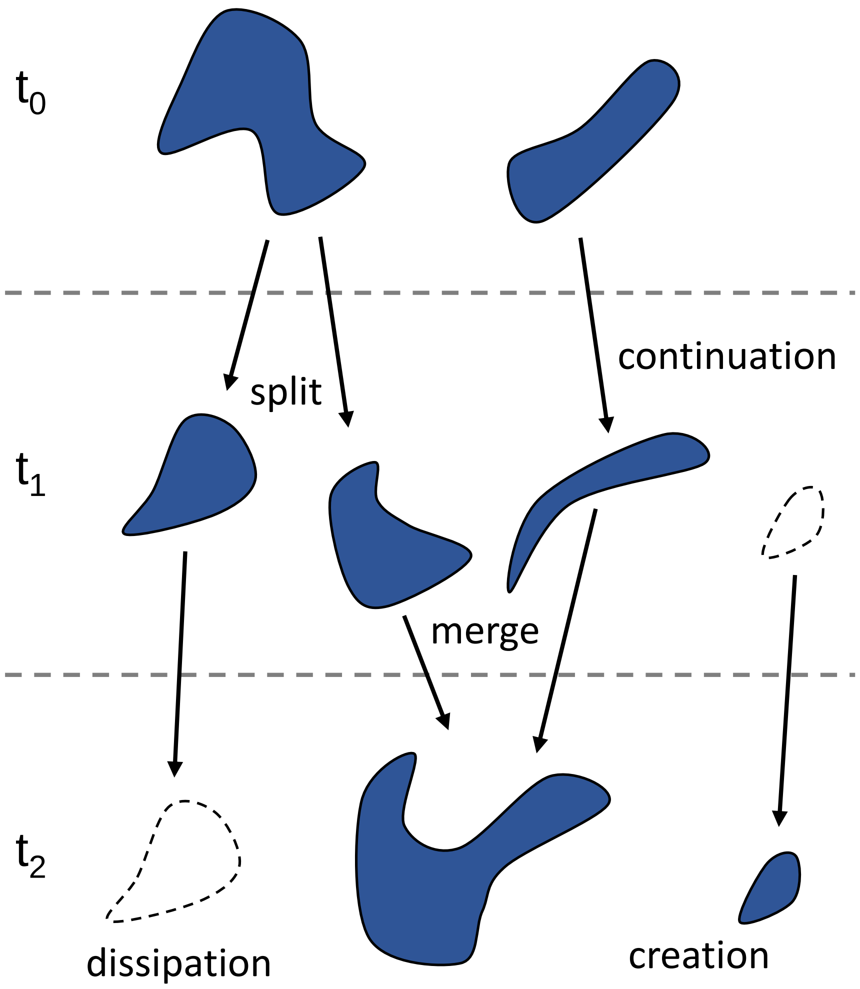
Visualization & Interface Design Innovation

Introduction: Feature Tracking

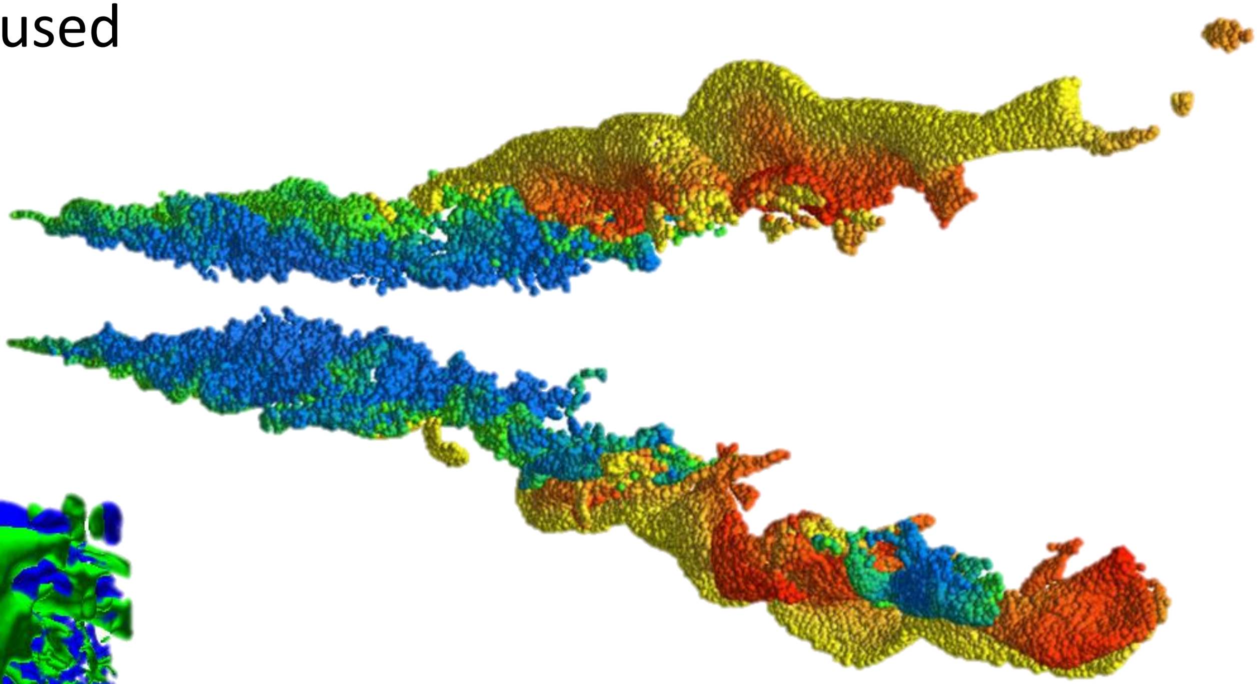
- Extensively used in the scientific community
- Connect features across multiple timesteps (snapshots)
- Different types of evolution
- Well established problem*
- Feature tracking concerns
  - Low temporal resolution
  - Large Scale Datasets
  - Missing data



*[Samtaney et al. 1994], [Silver and Wang 1994,1996], [Reinders et al. 1999], [Theisel and Seidel 2003], [Caban et al. 2007], [Muelder and Ma 2009]

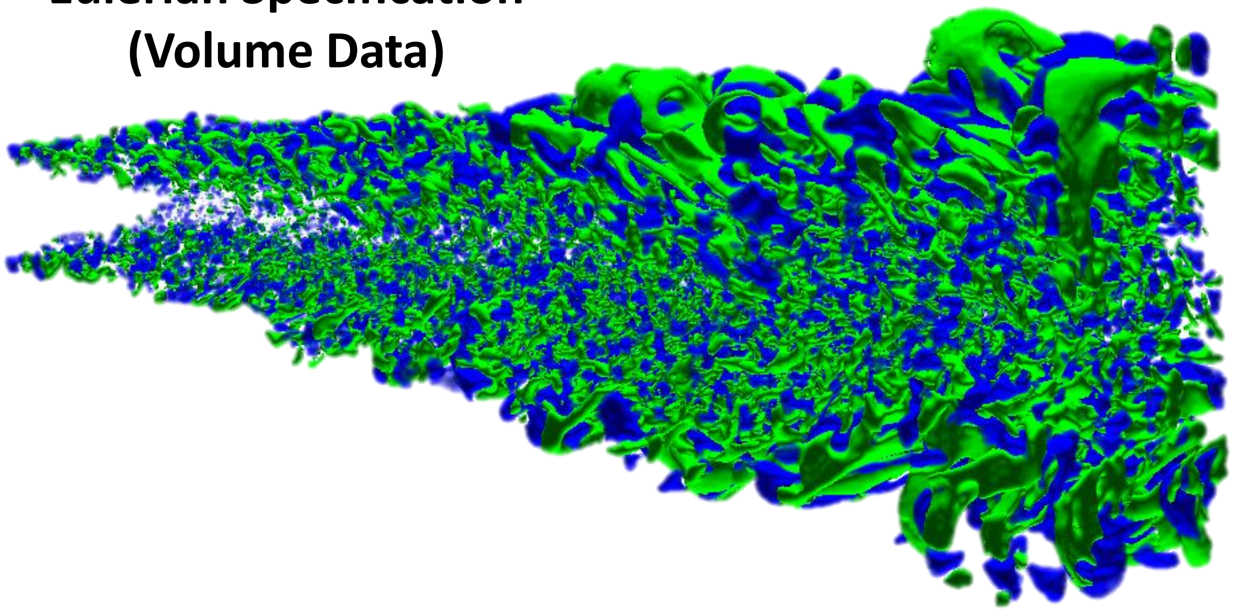
Introduction: Flow Specifications

- Hybrid simulation codes commonly used
- *Eulerian* Specification
- *Lagrangian* Specification



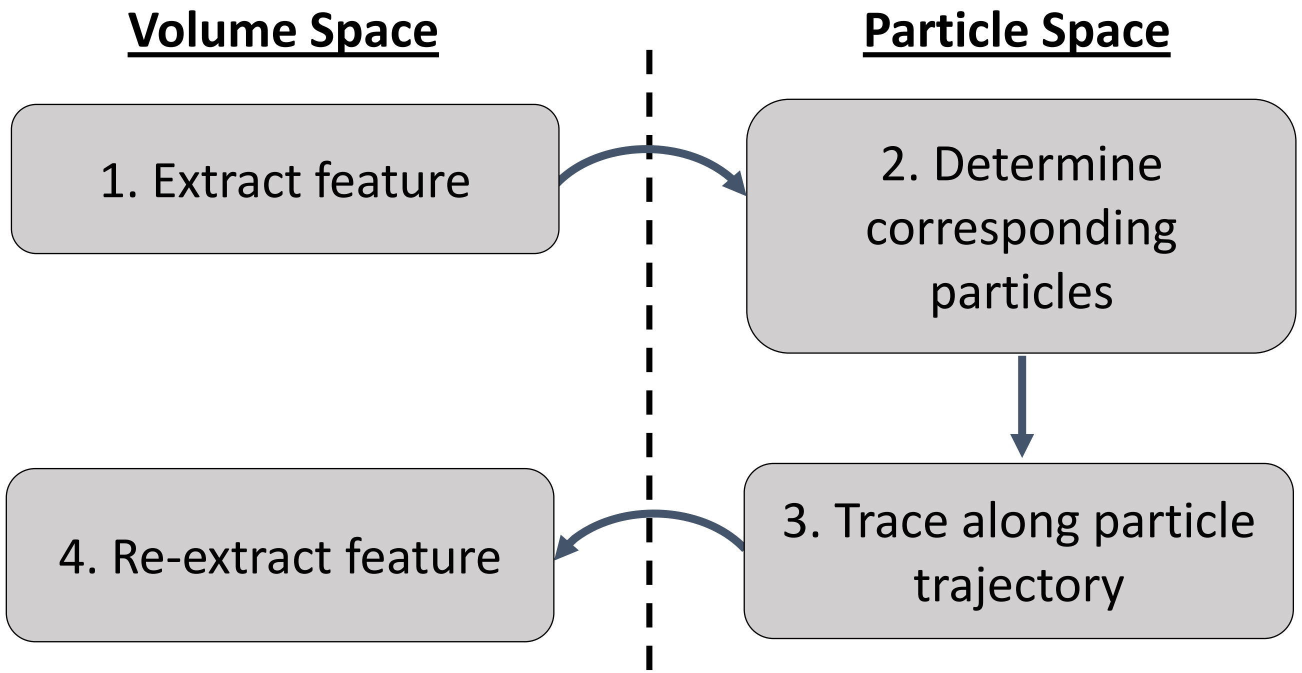
Lagrangian Specification
(Particle Data)

Eulerian Specification
(Volume Data)



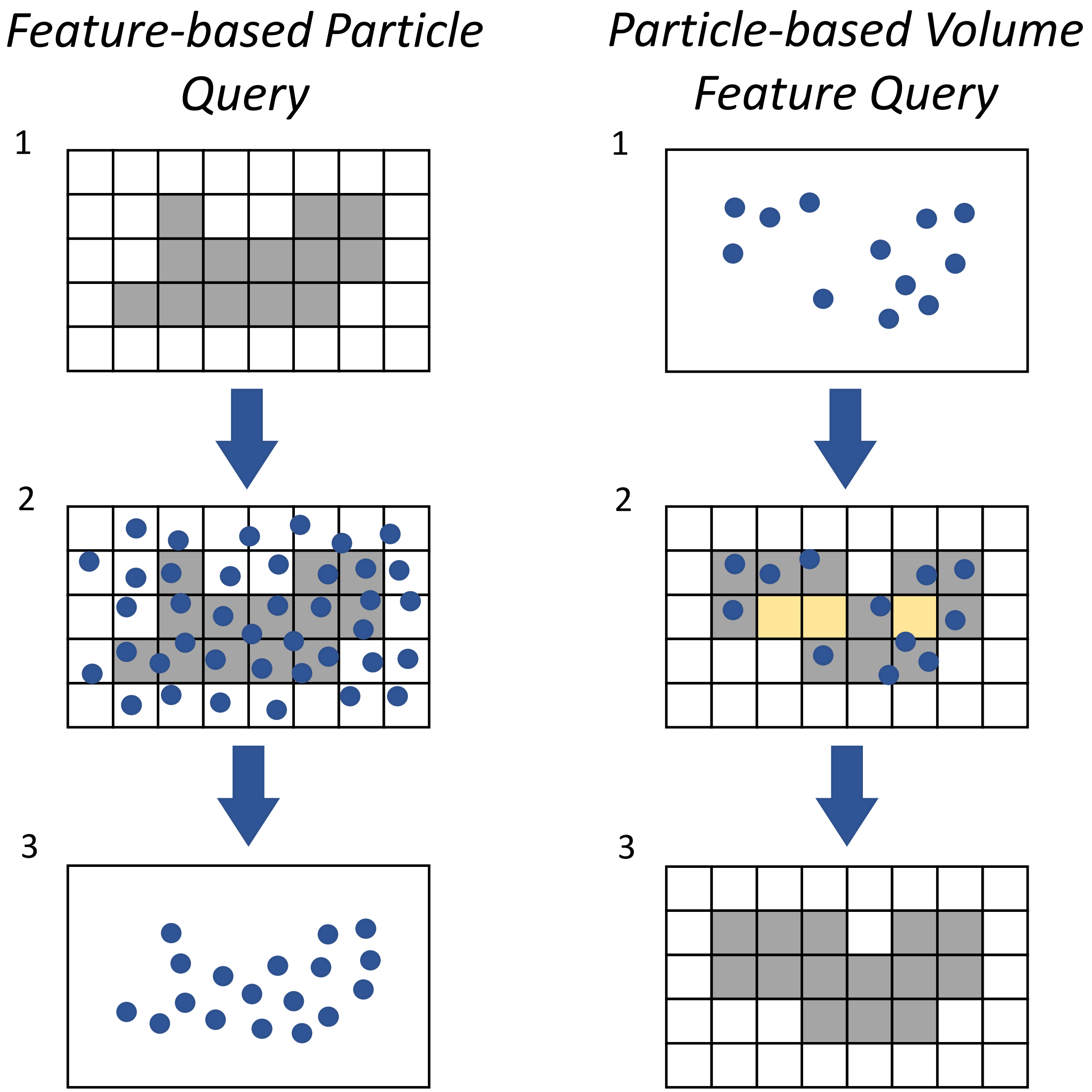
Method: Overview

- Utilize both specifications for more efficient tracking
- Switch between the different data spaces
- All “tracking” is done in the particle space
  - Particles are indexed
  - Easy to jump many timesteps into the future (or past)



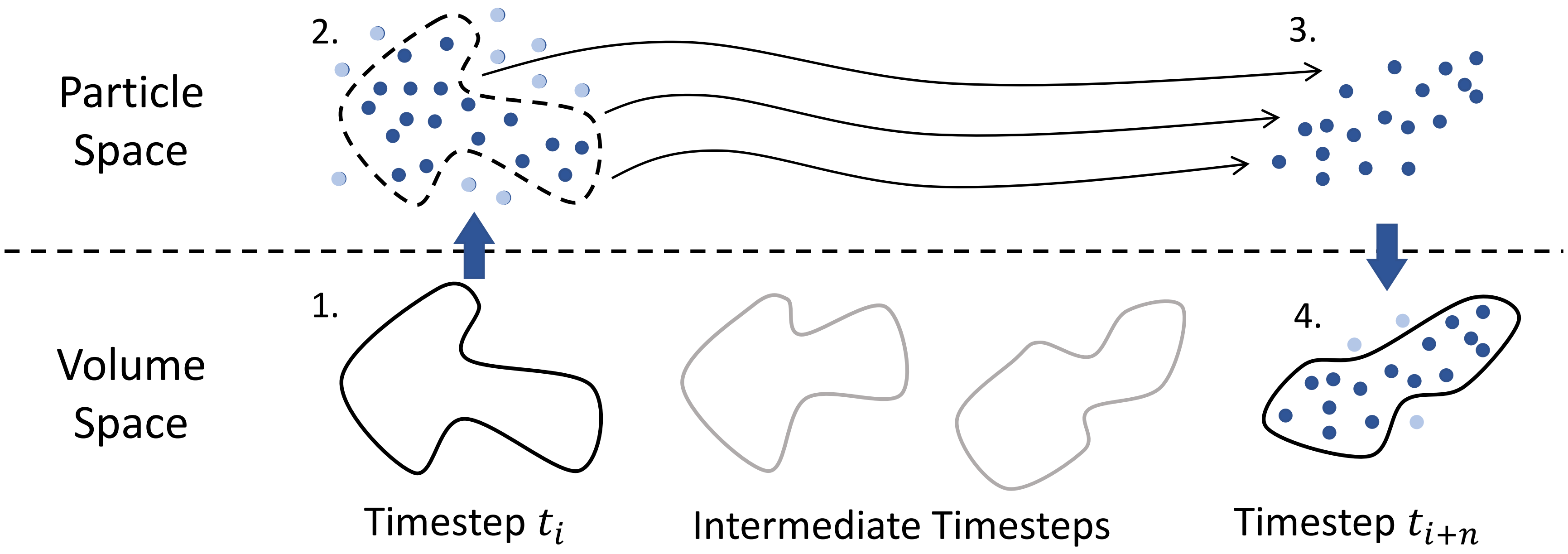
Method: Building the Correspondence

- Need to form a connection between the data spaces
- Query subsets from one dataset using information from the other
- Feature-based Particle Query
- Particle-based Volume Feature Query



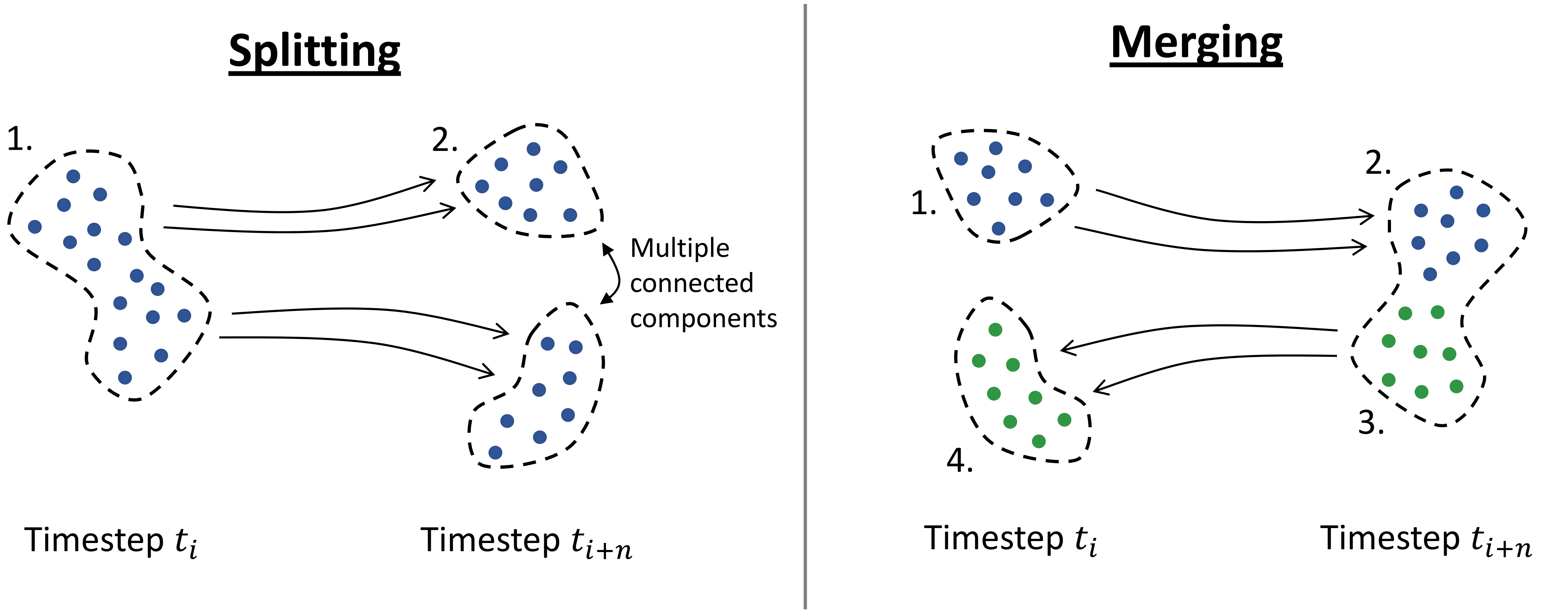
Method: Identifying Continuation

1. Identify/extract a region of interest using region growing
2. Determine corresponding particles
3. Trace particles along their trajectories via a jump to a later timestep
4. Re-extract feature based on new particle locations with mismatched particles discarded



Method: Identifying Splitting and Merging

- Splitting: a single feature breaks off into two or more connected components
- Merging: two or more features combine to form a single feature
- Creation and dissipation



Method: Uncertainty Metrics

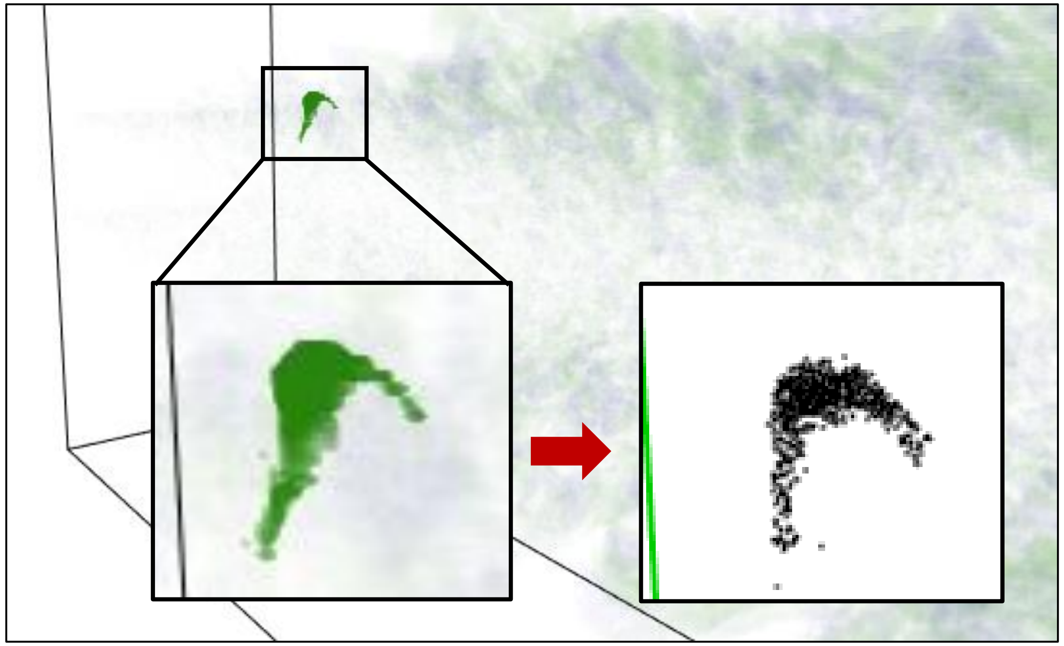
- Discrepancies between the data spaces can occur
  - Features can pop in and out of existence (particles might not)
  - Particles are often massless (features might not be)
  - Computation and interpolation errors
- Need a way to gauge the accuracy of our predictions
- Measure of "discrepancy" between the data spaces
  - The number of particles that fall outside the feature should be small
  - But account for the fact the features can dissipate

$$D = \max\left(\frac{|p'|}{|p|} - \max\left(1 - \frac{V_{i+n}}{V_i}, 0\right), 0\right)$$

p: original set of extracted particles
p': set of particles that fall outside feature
V_i: volume of feature at timestep i

Results: Combustion Dataset

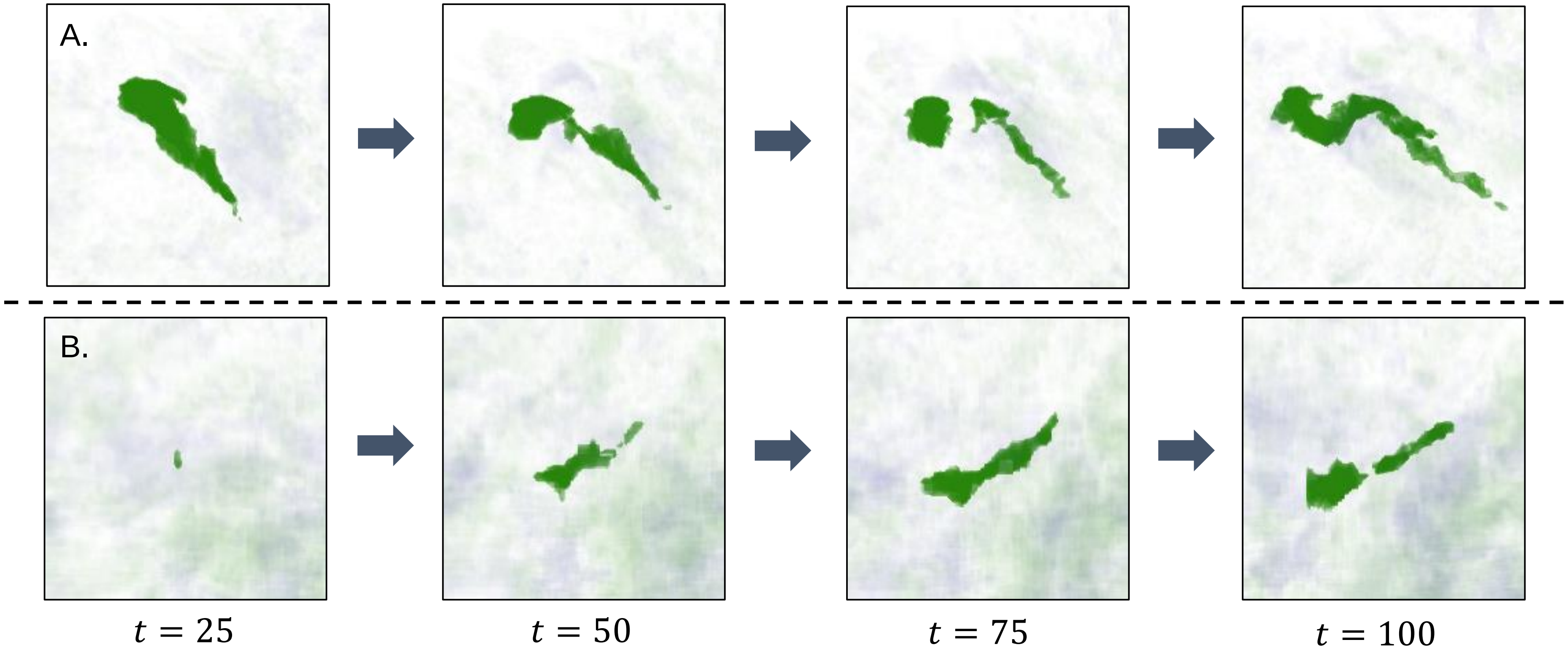
- S3D, a 3D peta-scale simulation developed by Sandia National Labs*
- Volume Data
  - Scalar field
  - Characterized into 27 different flow classifications
- Particle Data
  - Massless tracers
  - Measure many variables (temperature, molecular mass fractions, etc.)



*[Yoo et al. 2011]

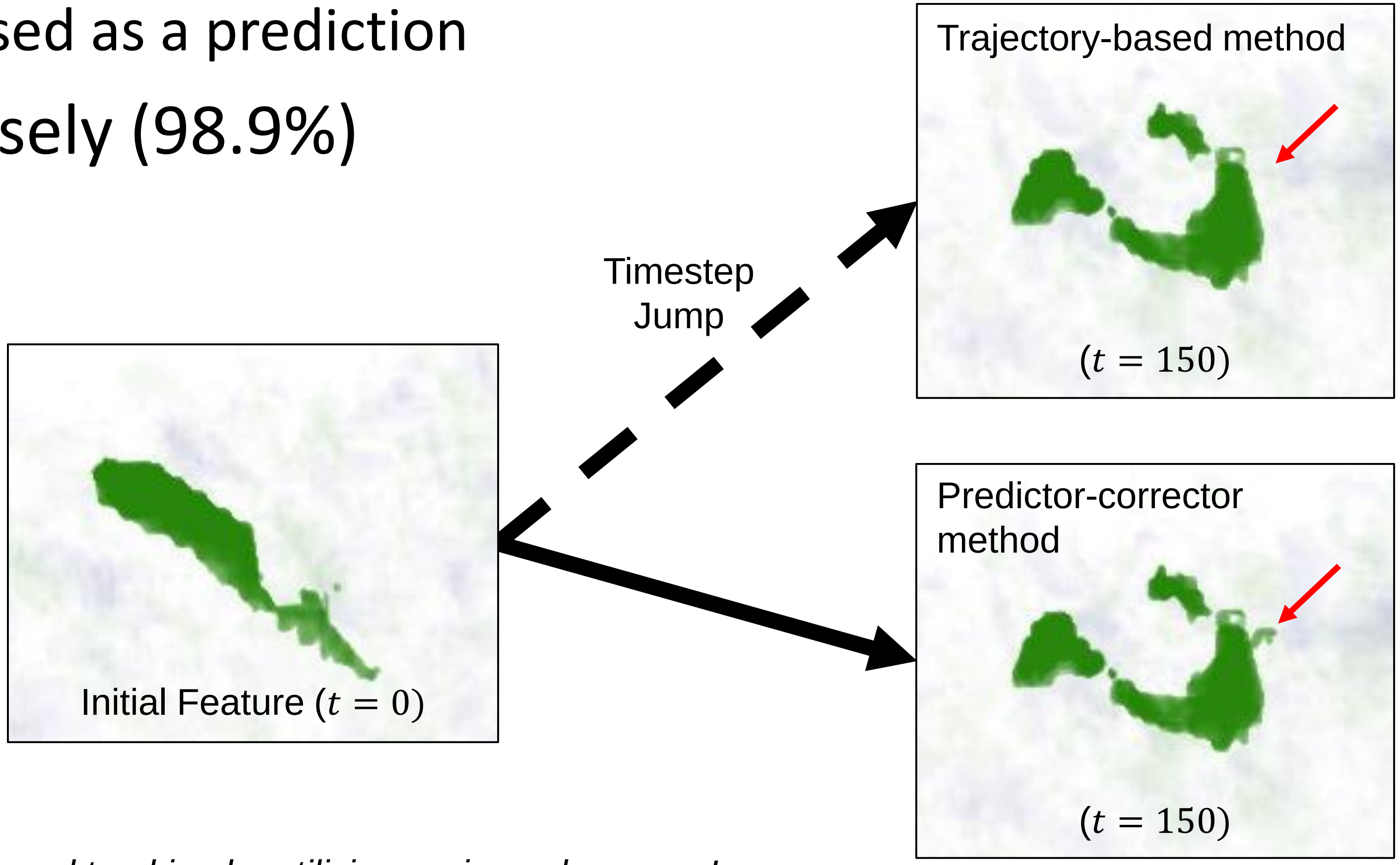
Results: Combustion Dataset

- Initial particle extraction at timestep 25
- Jump 25, 50, or 75 timesteps to produce later feature
- Continuation, splitting, merging, and creation are visible



Results: Technique Comparison

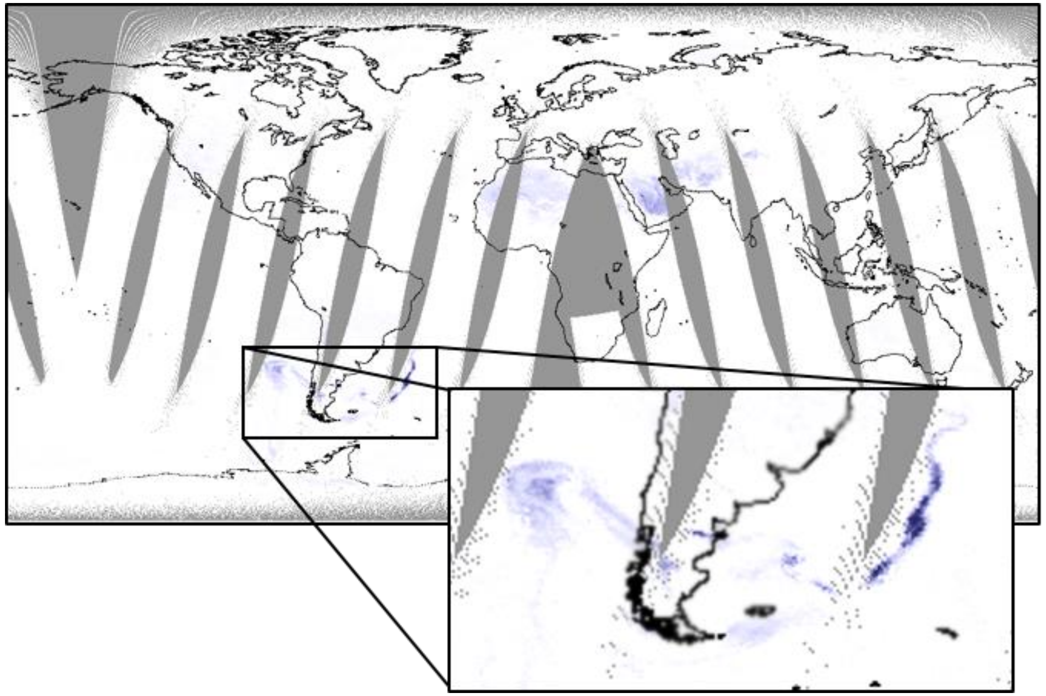
- Compare to an existing technique (predictor-corrector method*)
  - Uses region growing and refinement to connect features
  - Previous timestep is used as a prediction
- Results match very closely (98.9%)
- Timing results:
  - **TB:** 59 ms
  - **PC:** 541 ms

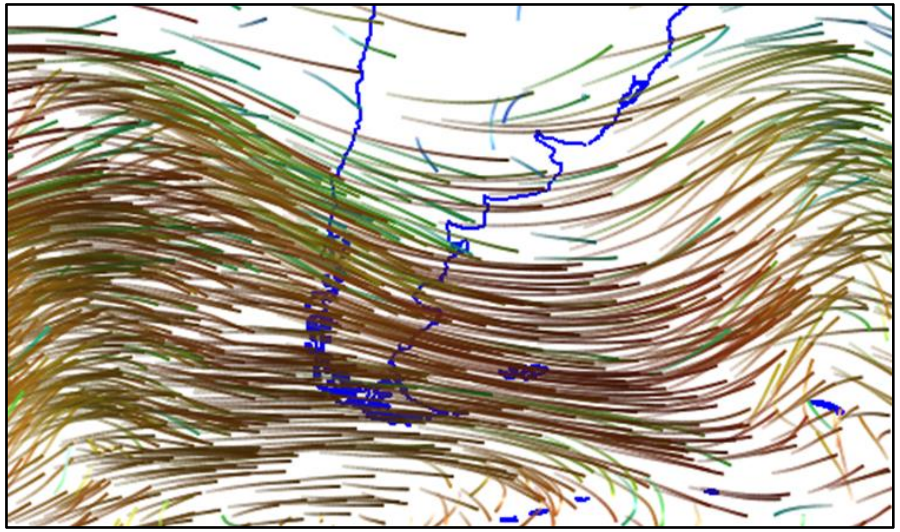


*C. Muelder and K.-L. Ma. *Interactive feature extraction and tracking by utilizing region coherency. In Visualization Symposium, 2009. PacificVis'09. IEEE Pacific, pages 17–24, April 2009.*

Results: Atmospheric Dataset

- "Volume Data" (in this case 2D)
  - Satellite ash detections from NASA's Atmospheric Infrared Sounder*
- Particle Trajectories
  - Chemical Lagrangian Model of the Stratosphere, Research Center Jülich*
- Large areas with missing data due to satellite limitations

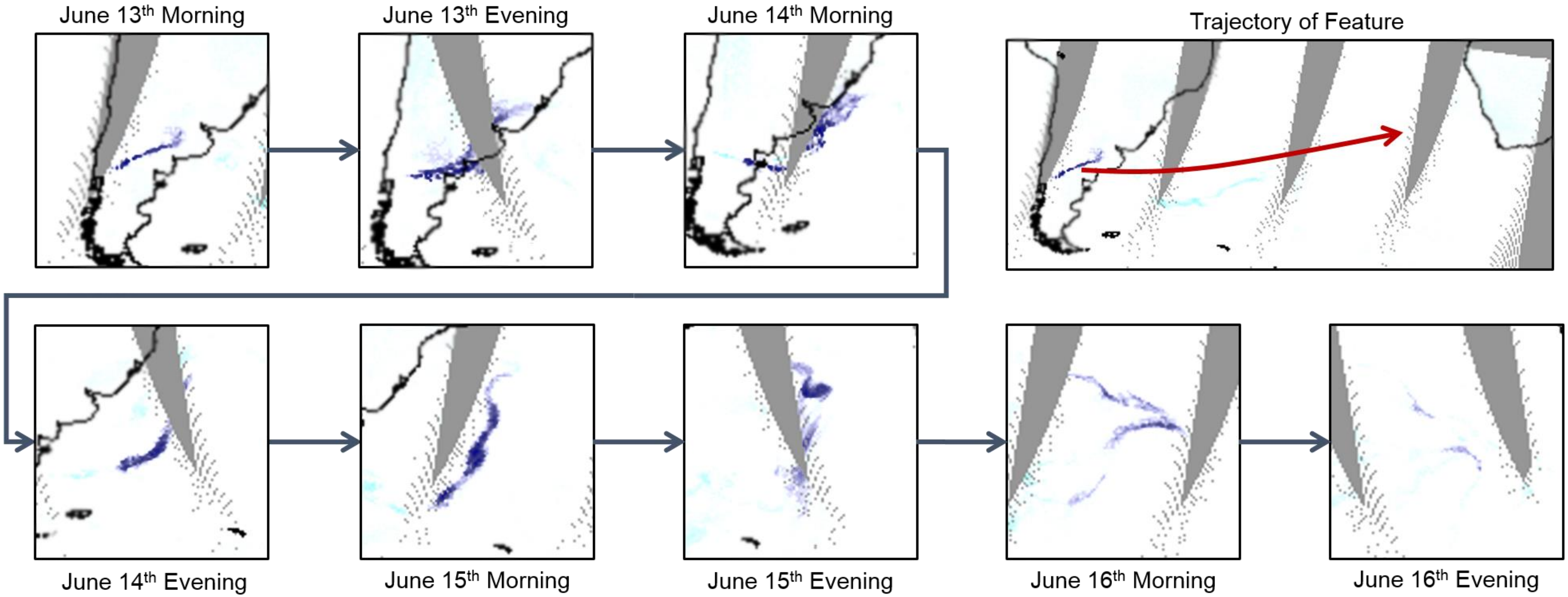




*[Hoffman et al. 2014], [Griessbach 2012,2014]
[McKenna et al. 2002], [Ploeger et al. 2012]

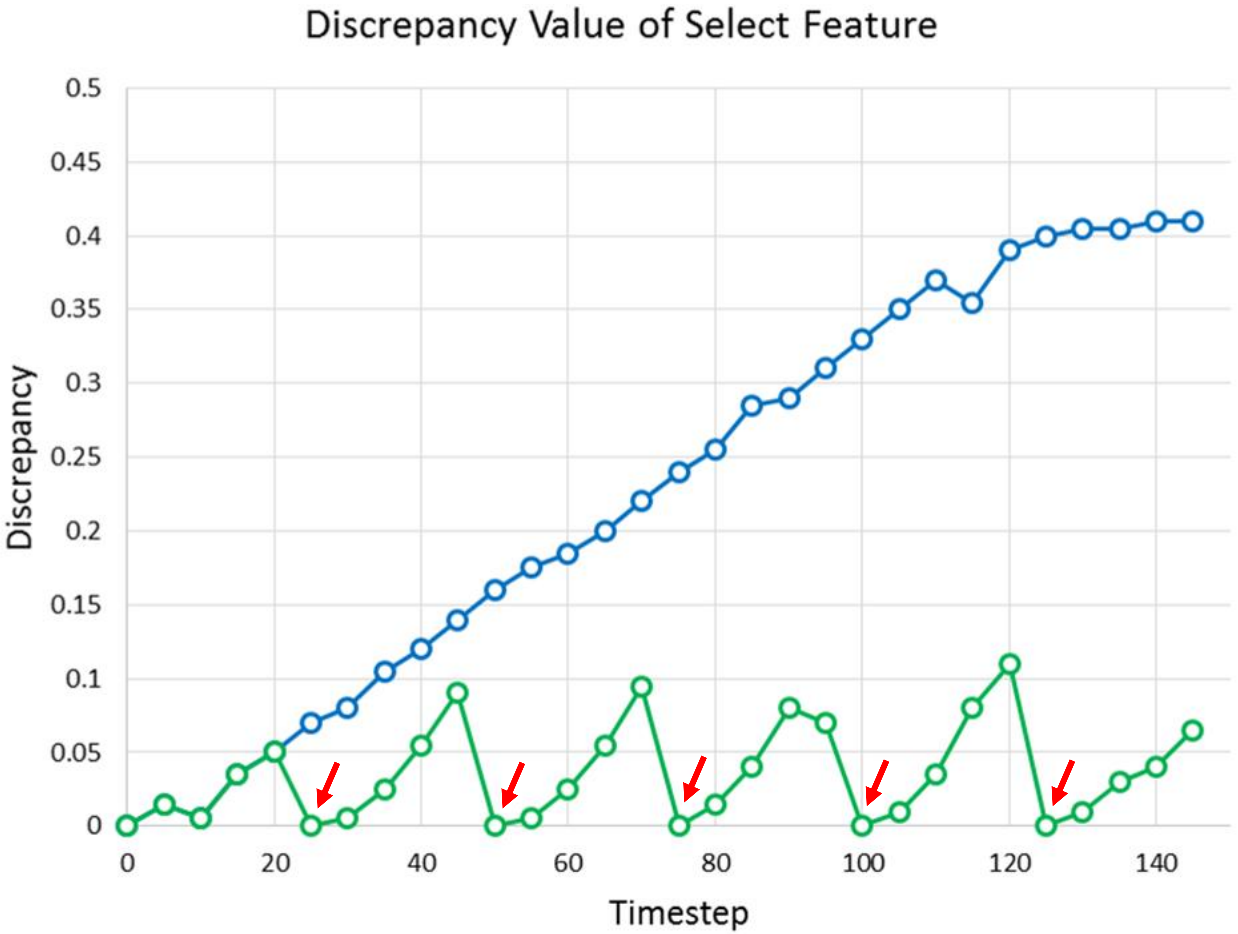
Results: Atmospheric Dataset

- We can track ash clouds that pass through the missing regions
- Cloud travels East over the South Atlantic before dissipating



Discussion: Discrepancy Measure

- Re-extracting particles can keep the discrepancy low
- Users can choose balance between performance and accuracy



Blue:
Extract particles at first timestep and use same particle set to identify features at all subsequent timesteps

Green:
Re-extract new particle set from the identified feature every 25 timesteps (resynchronize particles with feature)

Conclusion

- Present a new trajectory-based feature tracking technique
  - Big Data → efficient tracking, lower I/O frequencies
  - Missing Data → temporally, spatially
- Large improvement in time ↔ small decrease in accuracy
- Limitations
  - Only track features that move with the flow
  - Requires corresponding particle data (or vector field)
- Further study
  - Interpolate features in missing regions (temporally, spatially)
  - Use trajectory clustering to cluster features based on their spatial movement

Acknowledgements

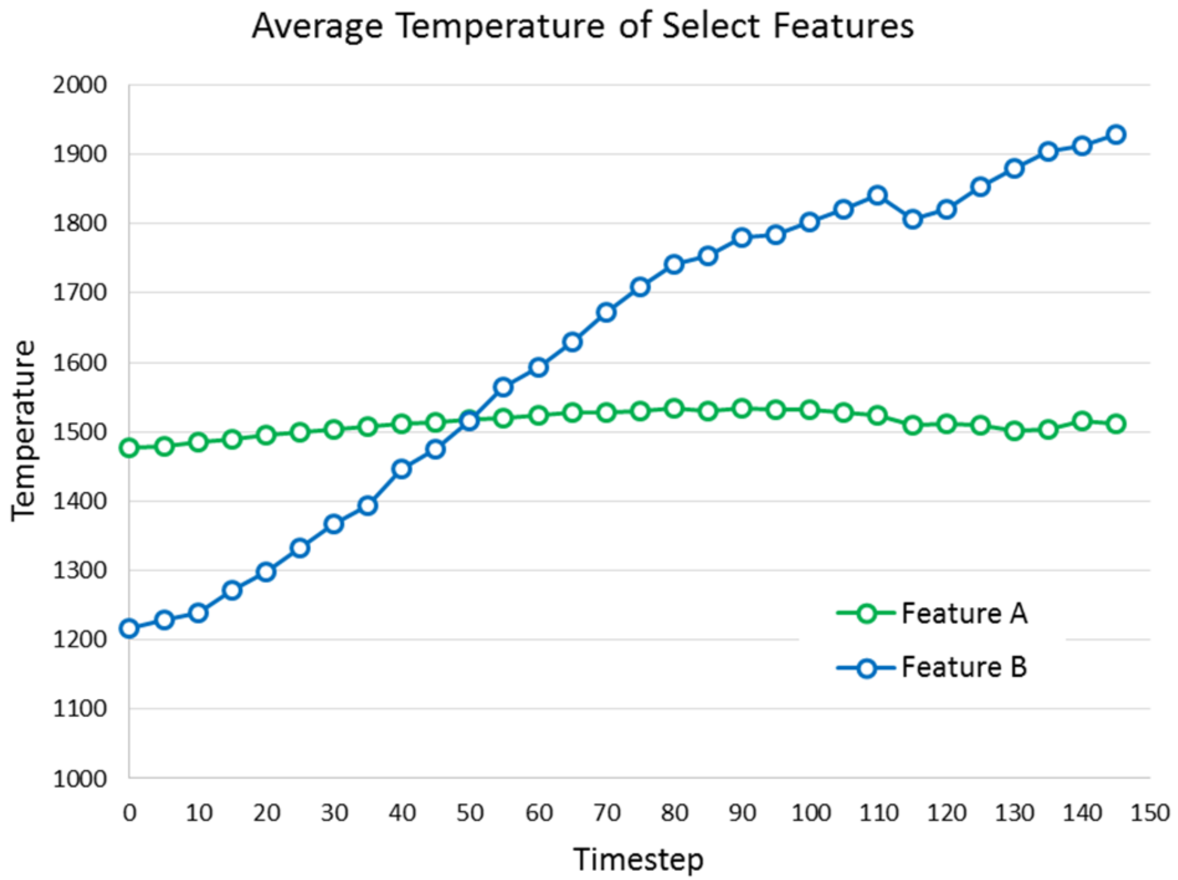
- Sandia National Labs (combustion dataset)
- SciVis Contest (atmospheric dataset)
- National Science Foundation through grants IIS-1320229, CCF-0938114, CCF-1025269, and IIS-1255237
- Department of Energy through grants DE-FC02-06ER25777, DE-CS0005334, and DE-FC02-12ER26072

Thank You

Questions?

Results: Combustion Dataset

- Measure the internal properties of a feature using the particles
- Don’t need to track the evolution of the feature through all intermediate timesteps



Discussion: Particle Density

- Compare against predictor-corrector method (ground truth)
- Artificially reduce the particle density (1/2, 1/4, 1/8, etc.)
- Compare a large feature (~500 voxels) vs. small feature (~10 voxels)