Deep learning for deriving sea ice drift from SAR data

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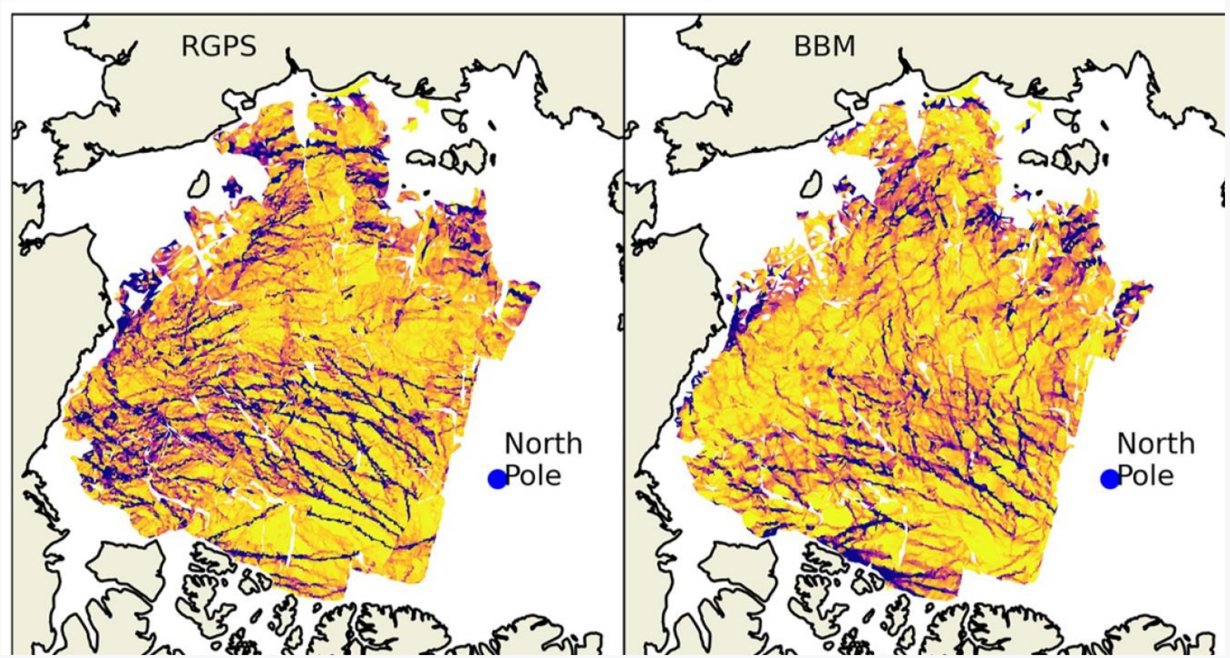
Background: We need a modern Lagrangian sea ice motion product

Author: Ron Kwok et al., JPL
Source: Radarsat-1 and 2
Years: 1996 - 2008
Content:

- Sea ice drift as <u>trajectories</u>
- Sea ice deformation

Resolution: 10 km
Frequency: 3 days
 # Citations: > 340

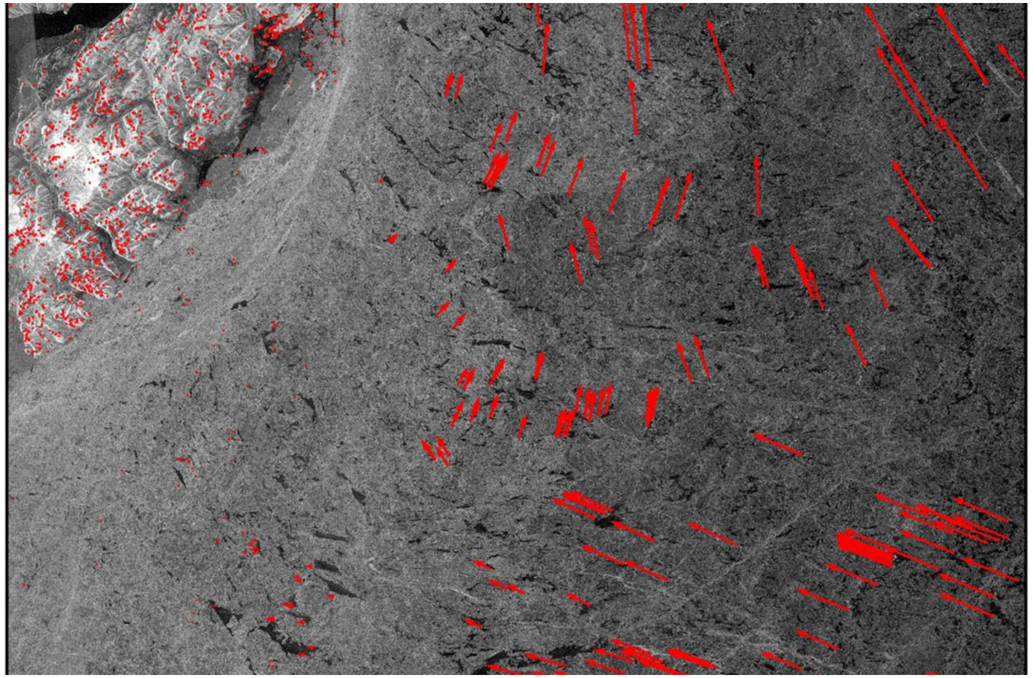
- **Essential for model validation**
- **Outdated**



Satellite observations   neXtSIM simulation

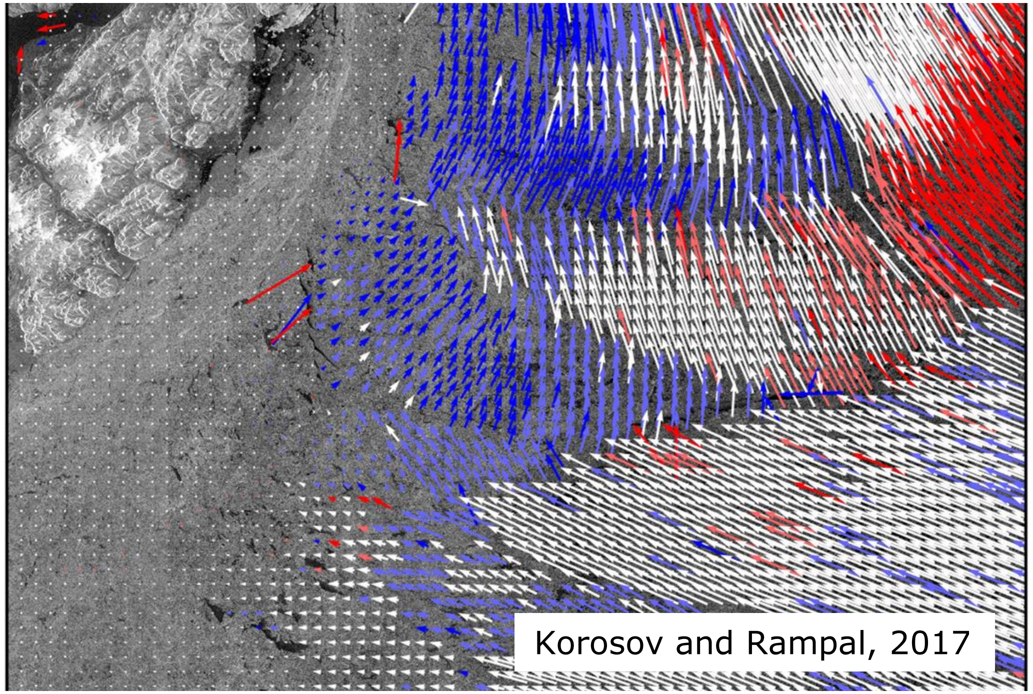
ARKTALAS CCN2 (ESA)**:** Time series of pan-Arctic Lagrangian ice motion from Sentinel-1

Combination of feature tracking and pattern matching for ice drift retrieval (LPS-2016)



1. Quick ~~and dirty~~ keypoint tracking

- Very fast
- Irregular and sparse vectors



2. Thorough pattern matching (max. cross-correlation)

- Ice drift vector in any point (e.g., regular grid)
- Where keypoints are sparse:
  - Slower
  - Lower accuracy

Can we use deep learning for deriving ice drift in any point of interest?

SuperPoint: Concept

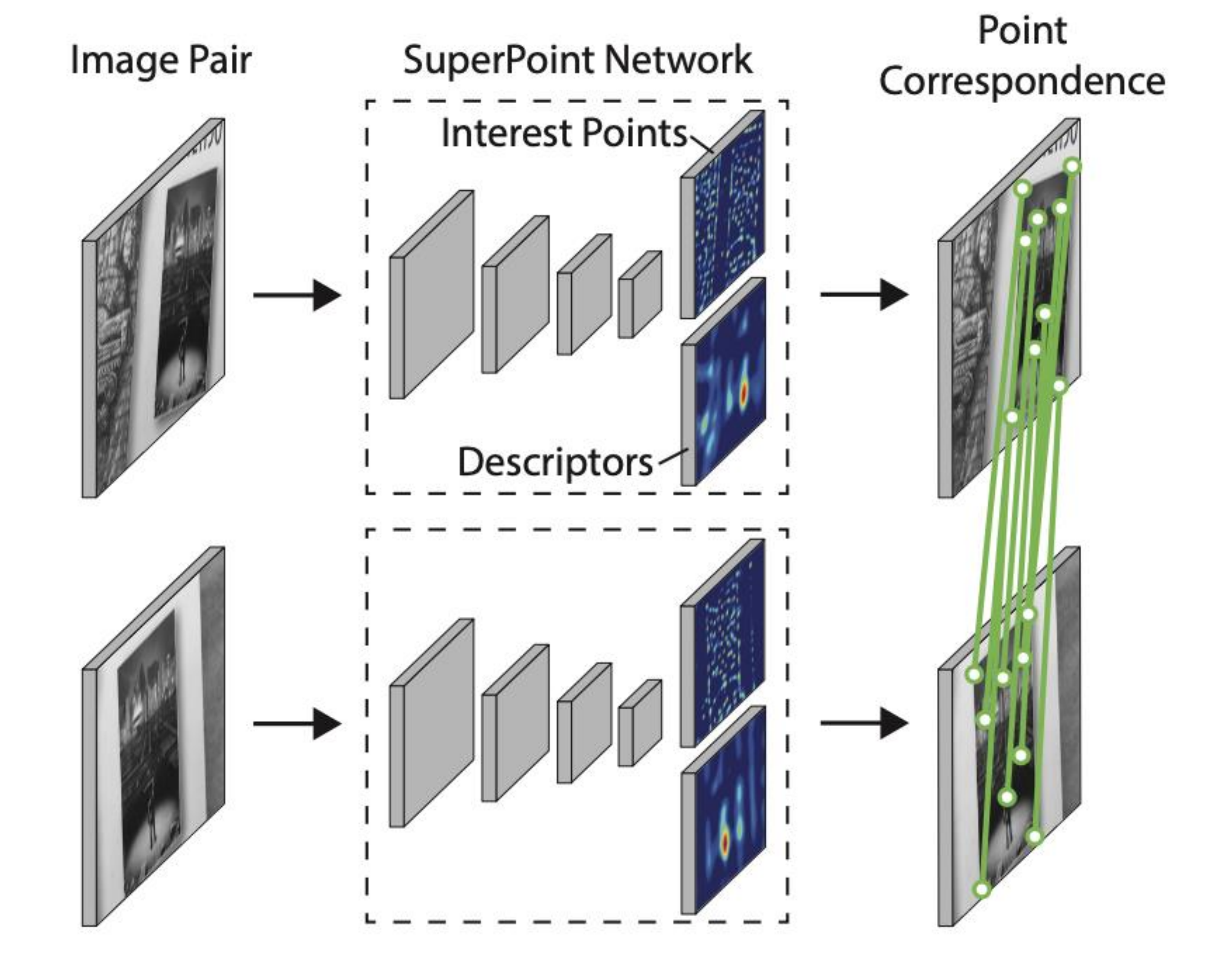


***Figure 1** from DeTone et al., SuperPoint: Self-Supervised Interest Point Detection and Description, 2018*

1. A pair of images is passed through a fully convolutional NN (Siamese NN).
2. The CNN returns scores (a map of keypoint probabilities) and descriptors (3D array with 256 descriptors for each keypoint).
3. Keypoints are matched by comparing the descriptors.

SuperPoint: Training

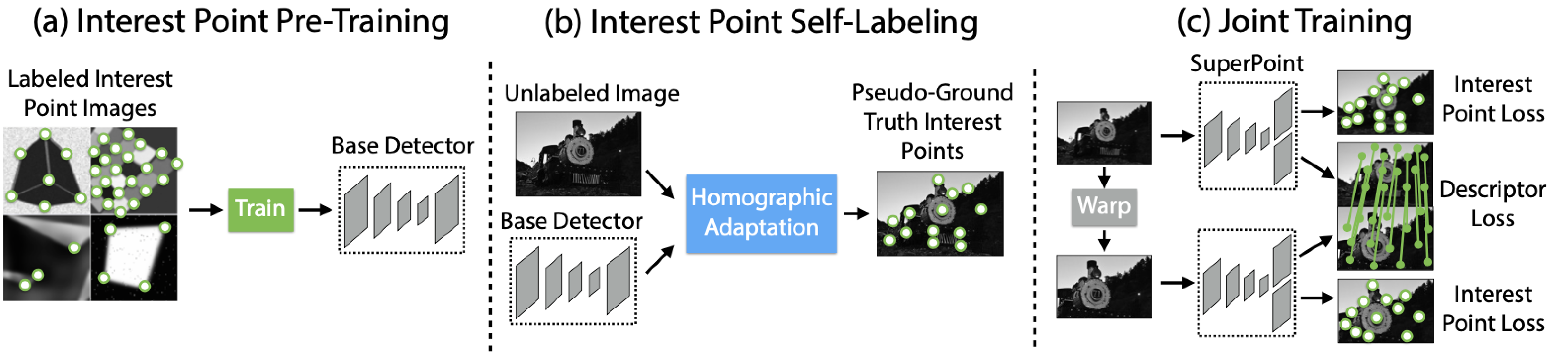


***Figure 2** from DeTone et al., SuperPoint: Self-Supervised Interest Point Detection and Description, 2018*

A) Synthetic images of various shapes are generated for pre-defined positions of keypoints. A base detector is trained with images on input and keypoint positions as targets.

B) Real image are processed with the base detector. Images and the results are warped (homographic adaptation). Thus, pairs of input images and target keypoints are generated.

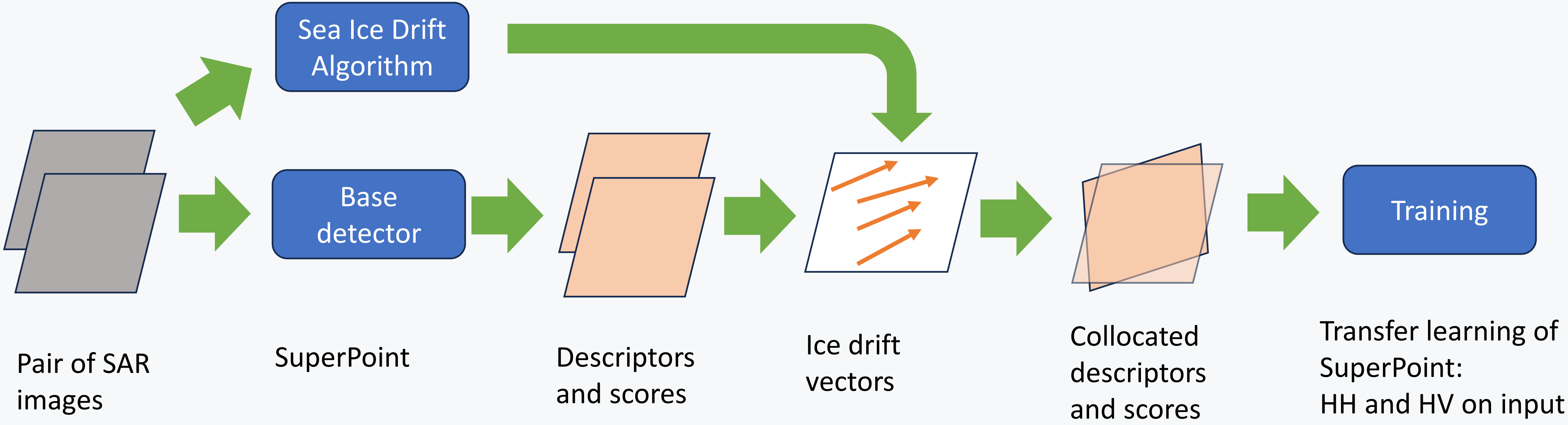
C) The pairs of images are used to train the descriptor retrieval CNN. Loss function: the difference of between matching descriptors is minimized and the difference between non-matching descriptors is maximized.

Training of the DL-based ice drift algorithm

Pair of SAR images

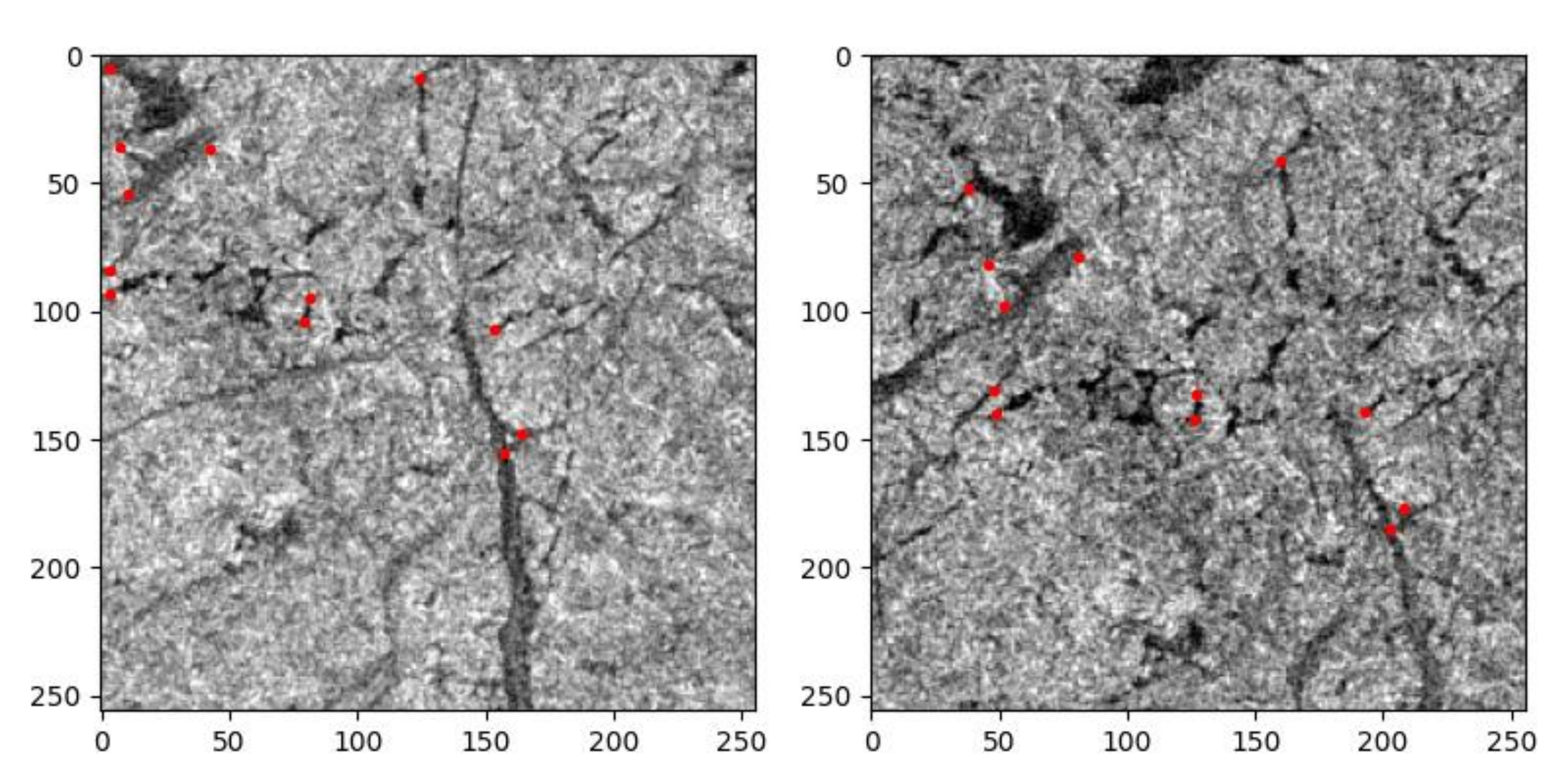
Ice drift vectors

Training of the DL-based ice drift algorithm



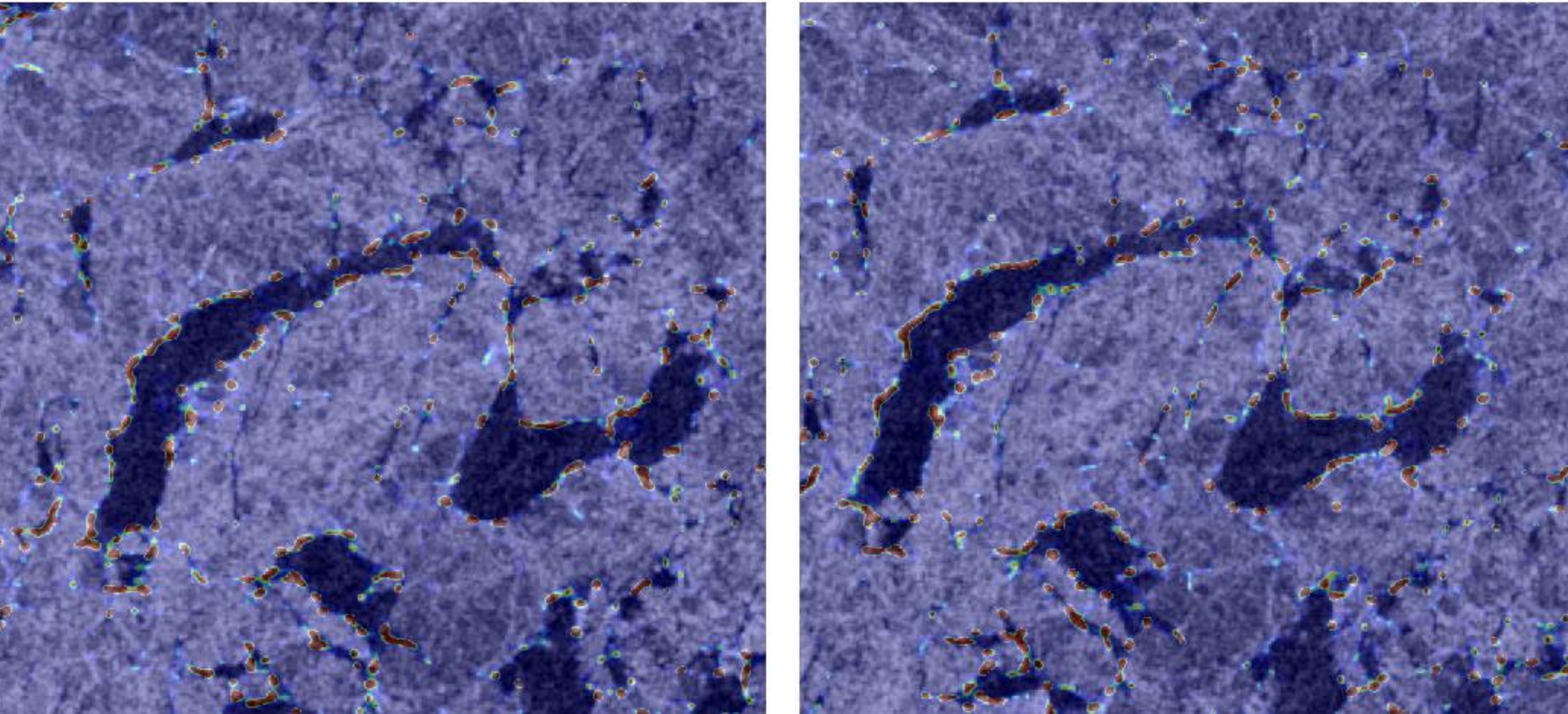
SuperPoint-based **L**agrangian **I**ce **M**otion algorithm: **SuperLIM**

SuperLIM training data

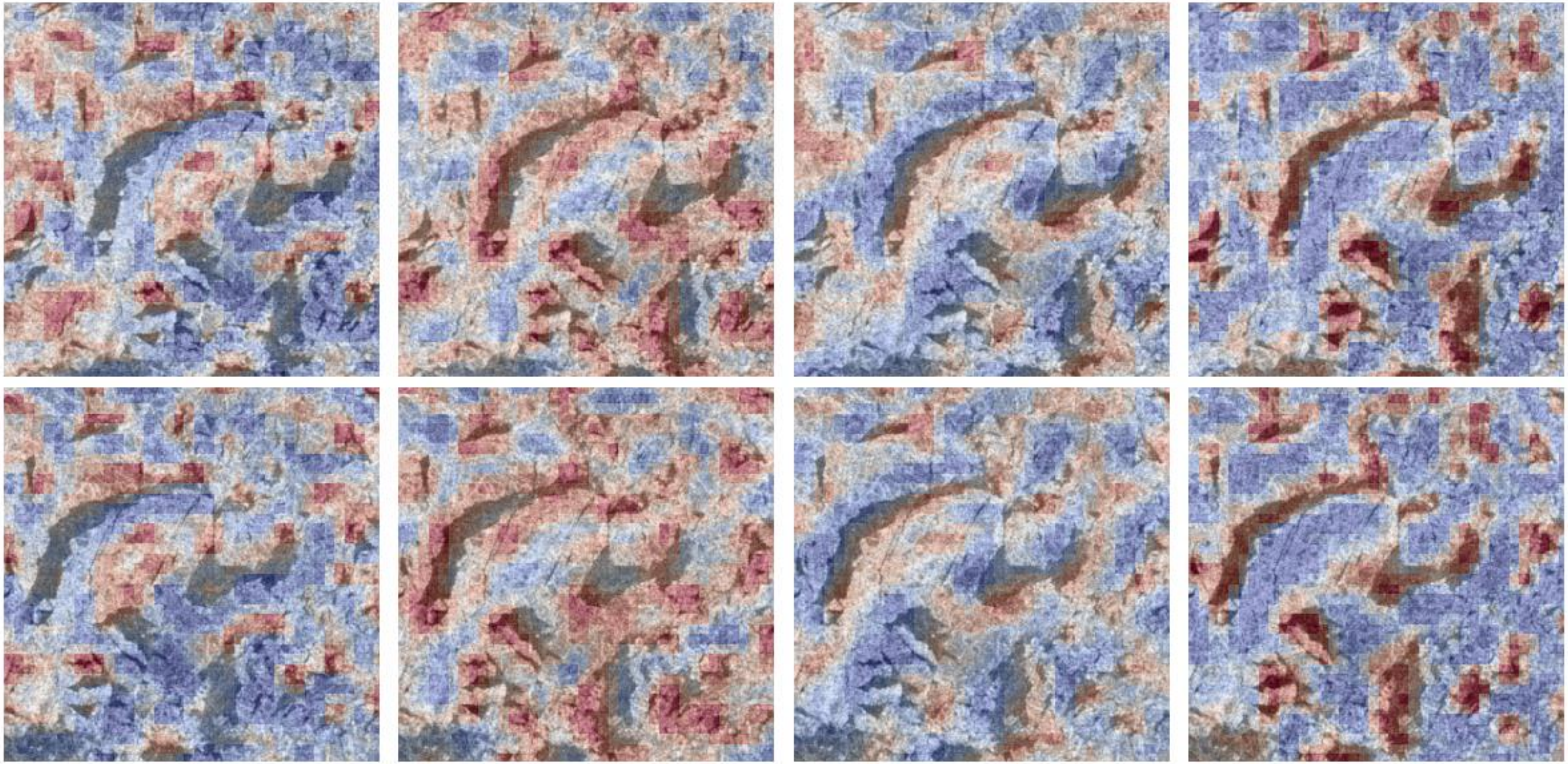


~2000 image pairs with 8 – 32 keypoints of pre-detected ice drift

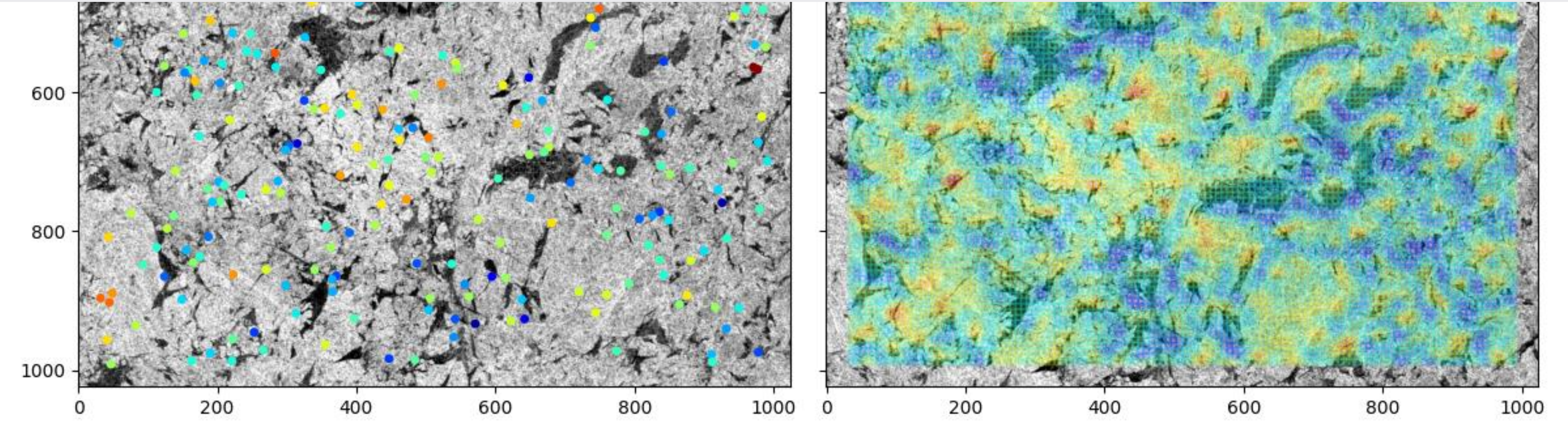
SuperLIM: keypoint scores for two sequential images



SuperLIM: maps of 4 descriptors for two images



SuperLIM: keypoint matching scheme

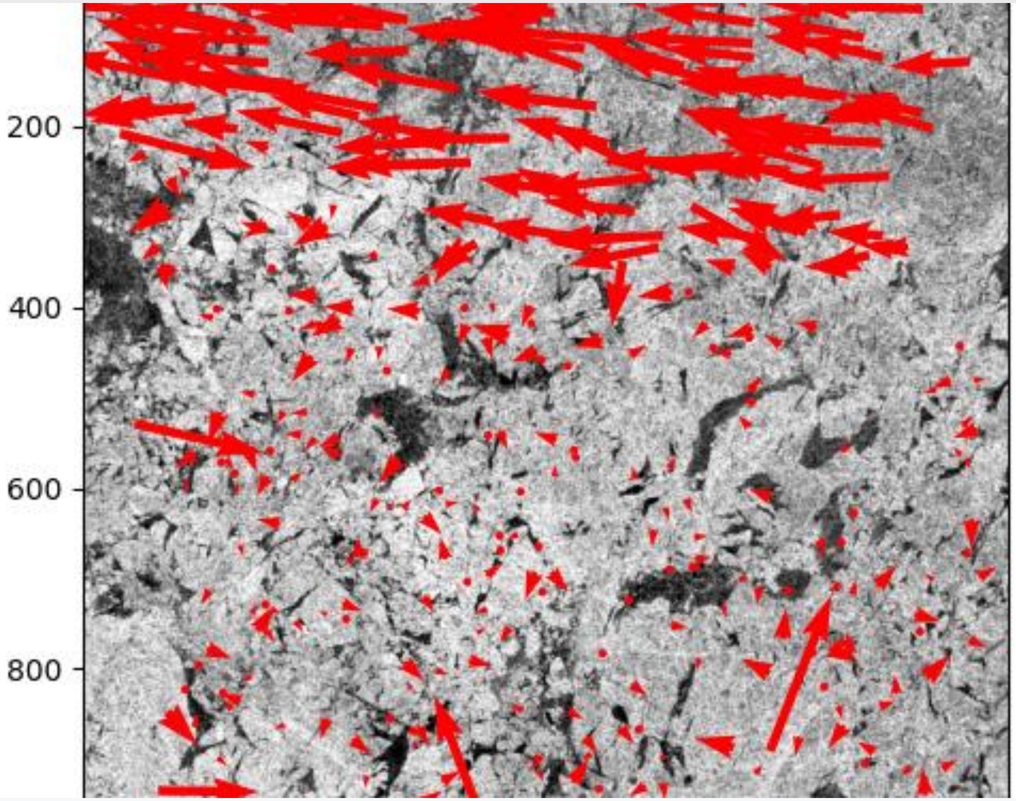


- On image 1 we seed keypoints in predefined locations.
- Descriptors are sampled on positions of keypoints using bilinear interpolation.

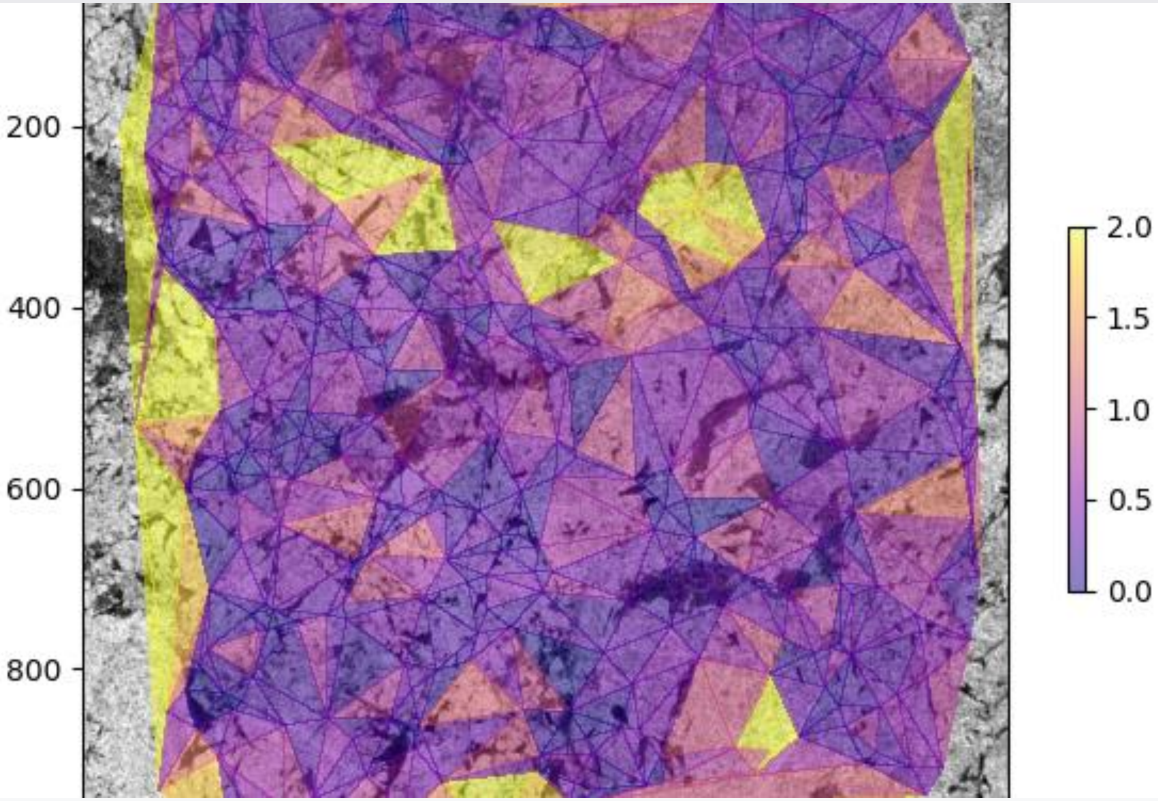
- On image 2 we use all descriptors from SuperLIM output.
- Descriptors are provided for every 8th pixel/row of SAR image.

Descriptors for keypoints from image 1 are matched with all descriptors from image 2.
We using brute force matching and apply spatial filtering (a KP is matched with only 100 nearest neighbors).

SuperLIM: accuracy of feature tracking



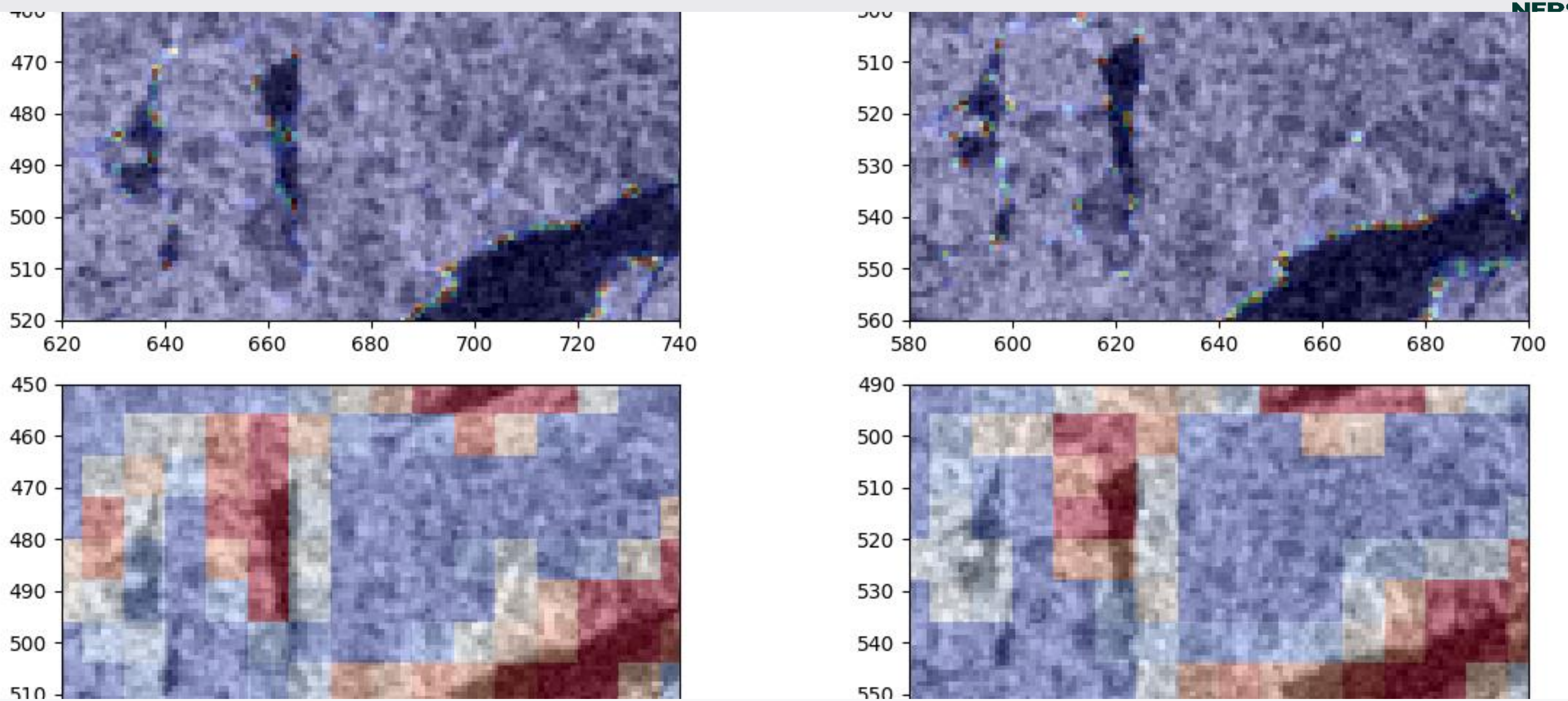
Ice drift vectors from SuperLIM keypoint matching



Sea ice deformation

Overall, the matching of feature descriptors works OK.
Most of the keypoints from image 1 have a corresponding keypoint on image 2.
However, when we compute sea ice deformation from ice drift we see a lot of noise.

SuperLIM: zoom on scores and descriptors



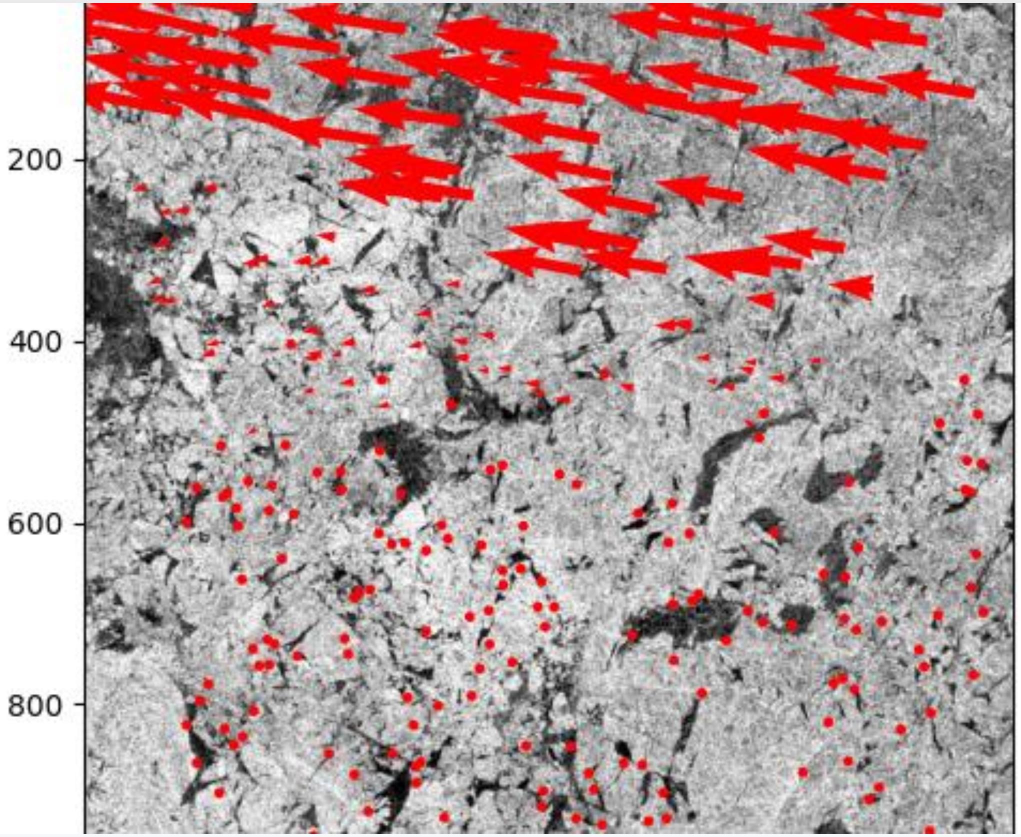
Revealed problems:

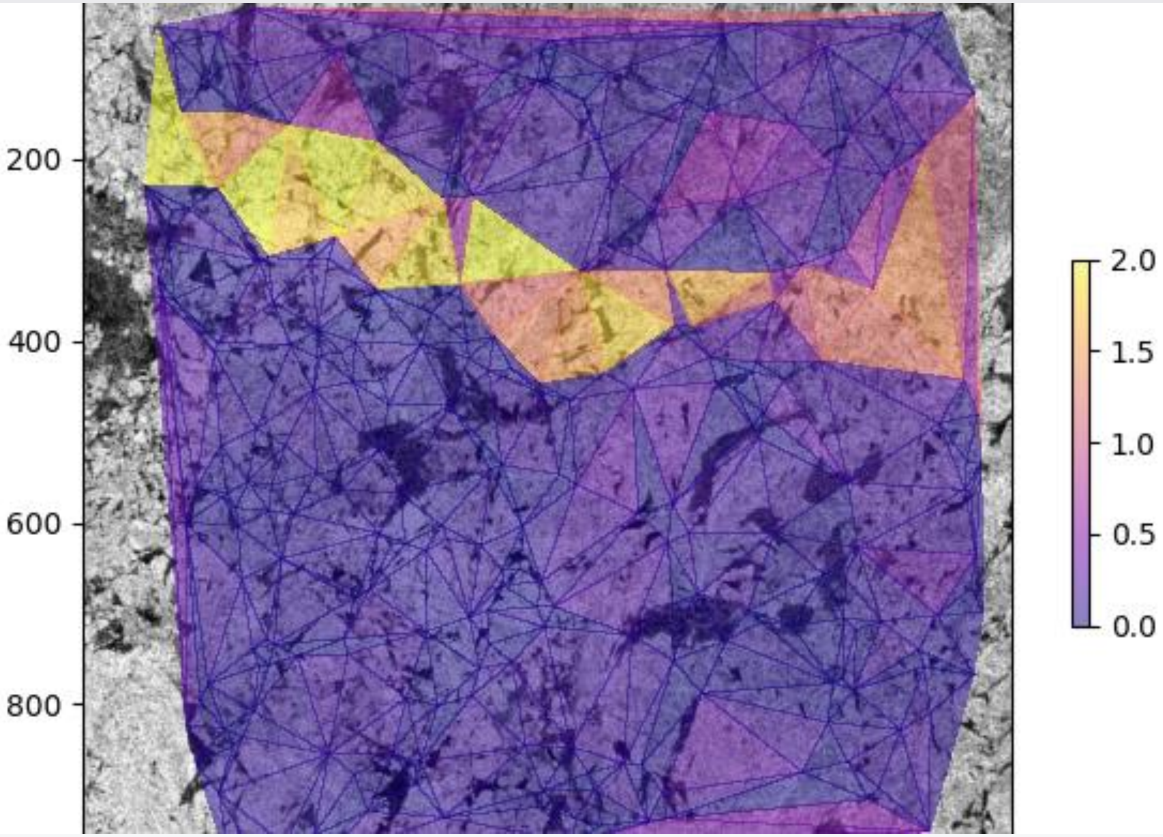
The keypoints are not located in EXACTLY the same pixel on two images.

The descriptors charachetrise a patch of 8 x 8 pixels.

Precision of FT is ~8 pixels?

SuperLIM: combination of DL feature tracking and pattern matching (MCC)





- The feature tracking derives the first guess drift vectors (precision ~8 pix)
- Then the pattern matching (max. cross-correlation) algorithm improves precision of each drift vector
- Searching distance for PM is small (16 pixels), therefore the speed is very high

Conclusions

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Yes, we can use DL for deriving sea ice drift, but …

- Precision of DL-based feature tracking is low (8 pixels, ~1.5 km).
- Speed of DL-based feature tracking is not very high (1 min for image pair). GPUs can be used.
- We use pattern matching after the feature tracking with a small searching window. It is very fast (2 sec).
- Combination of SuperLIM and pattern matching is rather fast and precise.
- SuperPoint is not rotation invariant. If SuperLIM is trained with rotation invariance, matching accuracy decreases. Workaround – providing information on ration as input to CNN. To be continued…

Thank you for attention!

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