

# Review of “Optical flow models as an open benchmark for radar-based precipitation nowcasting (rainymotion v0.1)”

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## Summary

The manuscript describes a Python-based open-source software package for radar-based precipitation nowcasting. Verification of the methods is done by using the DWD radar data, and an operational nowcasting product is used as the baseline method. To my knowledge, there is not any existing open source nowcasting library that is documented in the form of a scientific publication. Therefore, the paper makes a great contribution to the field. What also increases the value of the work is that the optical flow and extrapolation methods are based on ideas that have not been traditionally used in the field of precipitation nowcasting (i.e. using sparse feature extraction and forward extrapolation). However, I have some suggestions to improve the presentation of the work.

## Relation to previous work and literature review

- There are two important classes of optical flow methods that are only briefly mentioned or not mentioned at all:
  - In the variational methods, a smoothness constraint is added to the optical flow equations and they are solved "globally" over the whole domain. The key practical difference to the "local" methods, such as Farneback and Lucas-Kanade is that the motion field is automatically filled to areas of no precipitation.
  - In the spectral methods, the Fourier transform is applied to the inputs and the optical flow equations are solved in the spectral domain. The authors could add a citation to [3].
- There are several widely used optical flow algorithms developed in the machine vision literature. The authors could cite the Brox and CLG algorithms ([1] and [2]). These have also publicly available C implementations (see the IPOL journal).
- The paper cites to a large number of references where more advanced probabilistic nowcasting methods are described. Therefore, in the third paragraph of Section 6 the authors should be more concrete about future plans to include such features into rainymotion, and not just present ideas of potential improvements. Or will rainymotion be restricted only to deterministic extrapolation nowcasting based on Lagrangian persistence?

## Methodology

- Precisely speaking the Farneback optical flow algorithm is not global or dense and should not be called such. This misuse of terminology originates from the OpenCV library.
  - The Farneback method is dense only in the sense that it produces gridded output instead of motion vectors for sparse feature points as Lucas-Kanade does. If you look at the paper of Farneback, the method is formulated as local feature matching, where the solution of the optical flow equations is done by using a polynomial approximation. As

a result, the method produces zero motion velocities to areas of no precipitation. You can verify this by plotting motion fields produced by the Farnebäck method.

- It follows from the above that when a pixel is advected into area of no precipitation and a new motion vector is taken at that location (as in the DenseRotation method), its motion stops at the boundary. This could explain why Dense has in many cases better performance than DenseRotation.
- In Germann and Zawadzki (2002), the authors conclude that the backward semi-Lagrangian has better performance than the forward method. In fact, a majority of existing nowcasting methods use the former that is widely regarded as the best approach. However, here the authors use only the latter. If possible, the authors could also implement the backward method and include it in the performance comparison.
- Using the backward method would require filling the gaps in the motion field on areas of no precipitation. Otherwise, no precipitation would be advected into areas where it does not exist at the nowcast start time. A simple distance-weighted interpolation should be sufficient for this purpose. For the above reason, using gap-filling would also improve the performance of the forward semi-Lagrangian method.
- Note that the gap-filling is automatically done in the variational methods without the need for separate post-processing of the motion field. Therefore, such methods are truly dense and global. The authors could consider implementing a variational method and include it in the performance comparison.

## **The software library**

- Sections 2.4 and 3: Is the library restricted only to using the DWD data? Please add discussion about how to use the library with other file formats? For instance, by using wradlib this should be easily done because it supports a large number of different formats.

## **Verification**

- Section 2.6: MAE could be computed conditionally over those pixels where both the nowcast and the verifying observation exceed the detection threshold. Otherwise, there would be overlap with the CSI statistic as both penalize incorrect forecasts of precipitation/no precipitation.
- A large number of CSI and MAE statistics are shown for different lead times. There could be more analysis of the results.
  - There is no indication about what can be considered as a good CSI or MAE value for the nowcast to be usable. Can you give some thresholds?
  - The differences between the methods (excluding Persistence) are relatively small in terms of CSI and MAE statistics. Based on such differences, the authors should be more careful when claiming that some method is better than another. For instance the maximum mean difference between Dense and DenseRotation is only 0.01 according to Table 3.

- Figures 5-7 and p. 9, lines 19-21. The authors should indeed take a closer look on why the performance of the sparse methods is poor. Some comments about this:
  - The relevant parameter here is the number of features used in the tracking and nowcasting. If this number is too small, the motion vectors of the features are not representative of the large-scale motion field. Can you check this by adjusting the thresholds in the feature detector?
  - In addition, can you specify somewhere how many feature points are used with the sparse methods because this is a key parameter?
  - Another point missed in the paper is that the corner detector tends to pick features that have high intensities and gradients. Therefore, a very careful quality control is needed to ensure that the features are precipitation and not some random artefacts in the radar data. Can you be sure that the quality control is sufficient?
  - Even if the features are precipitation, they represent small-scale phenomena that can have very different motion from the large-scale advection field. Thus, the representativity of such features can be very poor.
- Forecasting the occurrence of precipitation/no precipitation for high intensities is highly relevant for practical applications. Therefore, I would suggest moving the results with the 5 mm/h threshold from the supplementary material to the main paper.

## Figures

- Since the motion field determination plays a key role in the paper, the authors should show at least one figure with an observed precipitation field and the computed motion field plotted on the same figure. Even better would be a figure showing motion vectors of features and motion fields computed by using different methods.
- Figure 4: Are names of individual functions relevant here? Consider removing them.

## Minor details

- p.4, lines 3-6 and Figure 1: How exactly is the affine transformation matrix calculated. In particular, is a single matrix estimated for all features or is this done separately for each feature?
- p.5, line 24: Why the HDF5 file format was chosen? Please add some justification for this.
- p.9, lines 7-9: I don't understand what this means. Can you clarify?
- p.9, line 24: stochastic accounting <- stochastic modeling?

## References

- [1] T. Brox, A. Bruhn, N. Papenberg and J. Weickert, High Accuracy Optical Flow Estimation Based on a Theory for Warping, ECCV 2004: 8th European Conference on Computer Vision, Prague, Czech Republic, May 11-14, 2004. Proceedings, Part IV, 25-35, 2004.
- [2] A. Bruhn, J. Weickert and C. Schnörr, Lucas/Kanade Meets Horn/Schunck: Combining Local and Global Optic Flow Methods, International Journal of Computer Vision, 61(3), 211-231, 2005.

[3] E. Ruzanski, V. Chandrasekar and Y. Wang, The CASA Nowcasting System, Journal of Atmospheric and Oceanic Technology, 28(5), 640-655, 2011.

Image Processing On Line (IPOL):

<http://www.ipol.im/pub/art/2013/21>

<http://www.ipol.im/pub/art/2015/44>