A Dynamic Flexible State Model for Rainfall Nowcasting

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Acknowledgement: Royal Netherlands Meteorological Society (KNMI)

May 8, 2020

Why nowcasting?

- Prediction up to 6 hours (World meteorological organization)

Applications:

- Short-term weather predictions for air traffic control.
- Early warning systems for flooding
- Outdoor event planning
- Road conditions, traffic management

Principle of radar nowcasting

- Nowcasts are generated by extrapolating rain cells along the principal direction of motion assuming "Lagrangian persistence"
- No temporal evolution except for some random noise

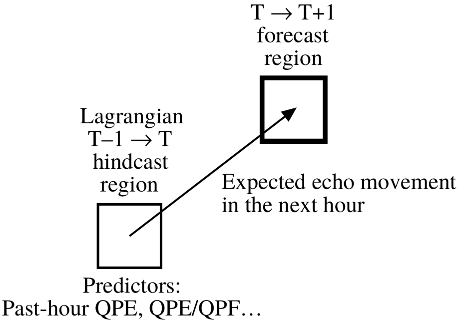


Fig: Radar nowcasting principle [Fabry *et al.*, 2009]

Nowcasting using radar: pros and cons

*A*dvantages:

- Computationally efficient
- High spatial and temporal accuracy (e.g. 1 km and 5 min)

*D*isadvantages:

- Radar data can be noisy (clutter, blockages, interference, ...)
- Vertical variability, attenuation, calibration, ...
- Radar does not measure rainfall rate but reflectivity. Z-R relation is sensitive to drop size distribution
- Can only predict what has already been observed. Predictions tend to lag behind true state.

State model formalism

- Target A and measurement area A^{0}
- Spatio-temporal rainfall field:
  $\mathbf{u}_t = [u_t(\mathbf{x}_1), \ldots, u_t(\mathbf{x}_N)]^{\mathrm{T}}$,
  $[\mathbf{x}_1, \ldots, \mathbf{x}_N]\ 2\ A$.
- $\mathbf{u}_t$ can be radar reflectivity or rainfall rate
- Dynamic model : $\boxed{\mathbf{u}_t = \mathbf{H}_t \mathbf{u}_{t\ \ 1} + \mathbf{q}_t}$
  $\mathbf{q}_t$: stochastic process noise.
- Estimation of N^2 parameters : computationally expensive for large A.

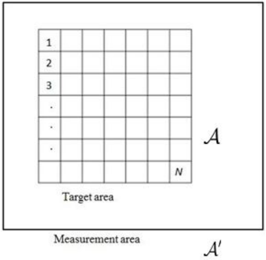


Fig: Target and measurement area

Estimation of H_t

- Estimation of $\mathrm{vec}(H_t)$ from $u_t = \underbrace{(u_{t-1}^T \otimes I_N)}_{N \times N^2} \mathrm{vec}(H_t) + q_t$.
- Simple(iterative) least squares approach:

$$\hat{h}_t = \arg\min_{h_t} \|u_t - X h_t\|_2^2, \quad (1)$$

where $h_t = \mathrm{vec}(H_t)$, and $X = u_{t-1}^T \otimes I_N$.

- For $H_t \approx H$ for $t = 1, \ldots, T_s$

$$X = \begin{bmatrix} u_0^T \otimes I_N \\ u_1^T \otimes I_N \\ \vdots \\ u_{T_s-1}^T \otimes I_N \end{bmatrix}_{NT_s \times N^2}, \quad (2)$$

- (1): single snapshot, and (2): multiple snapshot ahead prediction.

Generalized optimization problem to estimate H_t

- Underdetermined system of equations $\mathrm{u}_t = \underbrace{(\mathrm{u}_{t-1}^{\mathrm{T}} \otimes \mathrm{I}_N)}_{N \times N^2} \mathrm{vec}(\mathrm{H}_t) + \mathrm{q}_t$.
- Regularization using prior spatial information regarding $\mathrm{h}_t = \mathrm{vec}(\mathrm{H}_t)$, given by $f_p(\mathrm{h}_t)$. (e.g. sparsity, covariance structure)

$$\hat{\mathrm{h}}_t = \arg\min_{\mathrm{h}_t} [\underbrace{\|\mathrm{u}_t - \mathrm{X}\mathrm{h}_t\|_2^2}_{\text{Data}} + \lambda_{\mathrm{s}} f_p(\mathrm{h}_t)], \tag{3}$$

- Can also use predictions from a numerical weather prediction model):

$$\hat{\mathrm{h}}_t = \arg\min_{\mathrm{h}_t} [\underbrace{\|\mathrm{u}_t - \mathrm{X}\mathrm{h}_t\|_2^2}_{\text{Data}} + \underbrace{\lambda_{\mathrm{m}} \|\tilde{\mathrm{u}}_t - \mathrm{Y}\mathrm{h}_t\|_2^2}_{\text{NWP}} + \lambda_{\mathrm{s}} f_p(\mathrm{h}_t)], \tag{4}$$

where $\mathrm{Y} = \tilde{\mathrm{u}}_{t-1}^{\mathrm{T}} \otimes \mathrm{I}_N$.

- Weights λ_{s}, λ_{m} tuned based on the accuracy of NWP and prior.

Modelling rainfall dynamics using a scaled affine transform

- Assuming an affine transformation followed by scaling 6 (transformation) + 1 (scaling) parameters.
- Transform:
  $u_t(\tilde{\mathrm{x}}_j) = \alpha_t u_{t\;\;1}(\mathrm{x}_j),\ \alpha_t > 0,\ \tilde{\mathrm{x}}_j\ 2\ A$, where

$$\begin{bmatrix} \tilde{x}_i \\ \tilde{y}_i \\ 1 \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} = \mathrm{M}_t \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix}. \quad (5)$$

- Estimating the best α_t, M_t using consecutive snapshots.

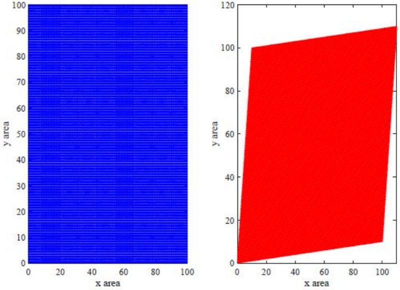
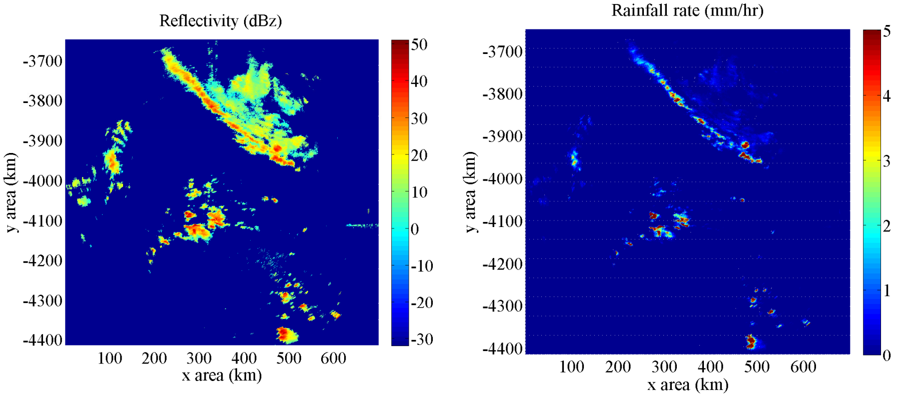


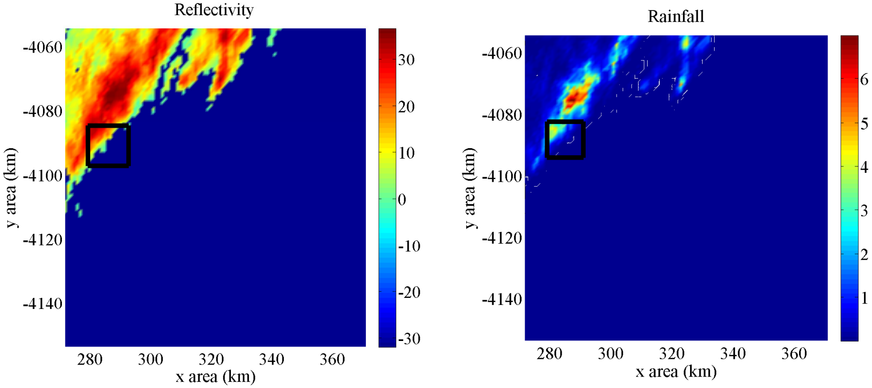
Fig: Affine coordinate transform

Total area : 700   765 pixels with spatial resolution 1 km^2.



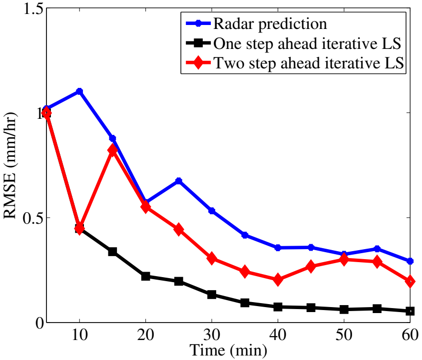
Selected measurement area and target area

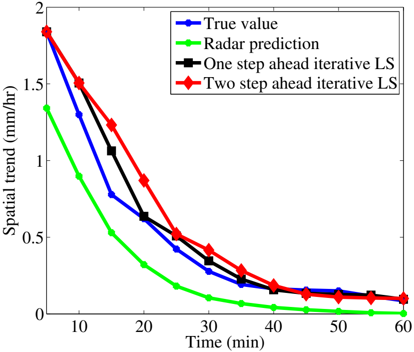
Measurement area : 100 100, Target area: 15 15.



Performance analysis

Used data: Rainfall Event from 03:30 - 04-30 a.m., 12.07.2019





Example of tracking the dynamics using affine transform (simulated field)

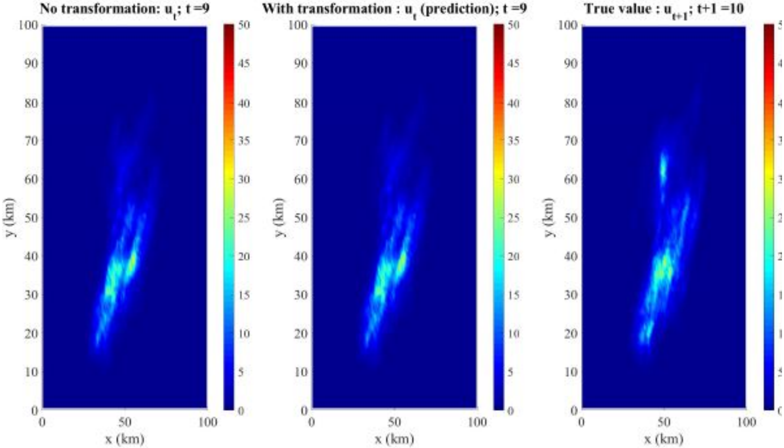


Fig: One step ahead prediction using the scaled affine transform model; No. of pixels: 100   100 can be predicted by only 7 parameters

Summary

- The regularized (iterative) least squares method outperforms Lagrangian persistence for single step ahead prediction. However, performance decreases for multiple step ahead predictions.
- Computational cost quickly grows with size of target area. Scaled affine transformations are less accurate but computationally more efficient.
- External information from NWP can be incorporated into the state model estimation problem using a multi-objective optimization framework.
- The combination of statistical radar extrapolation with physical knowledge from a NWP leads to better multiple step ahead predictions.