# Object-oriented processing of high-resolution precipitation forecasts by stochastic filtering

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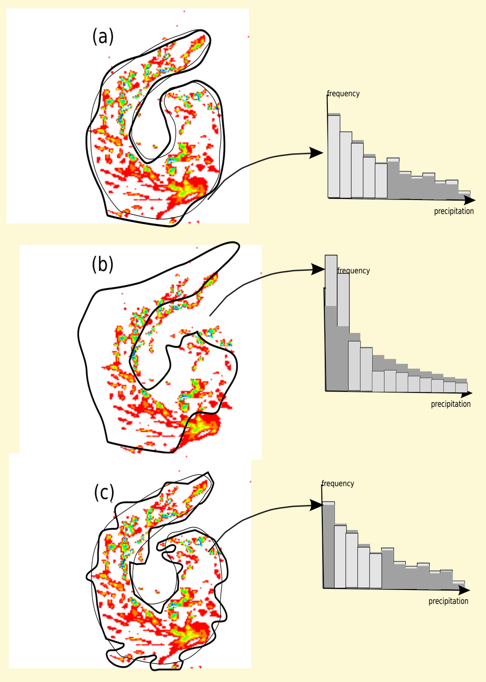
## 1. Introduction

The lack of dense observing netwoks for dynamical variables as well as microphysical ones leads to a relative poor predictability in current Non-Hydrostatic models at the km scale resolution. Although these models succeed in simulating a wide variety of convective situations, they eventually fail to represent mesoscale features at the appropriate location or appropriate time. Thus, the need for advanced postprocessing method is obvious and has been pointed out by numerous papers on mesoscale forecast verification in the recent past.
We introduce a method of mesoscale precipitation forecast (here outputs from the AROME model at 2.5 km resolution: Seity et al., 2011) post-processing based on the following main features: (i) the method runs at a coarser resolution than the model itself, (ii) it is based on an object-oriented approach in which the property of the object is the probability density function of the precipitation field inside the object, summarizing the rich forecast signal at full horizontal resolution, (iii) the object is a closed smooth curve which is tracked using a displacement field provided by an optical flow technique, (iv) uncertainties regarding the shape and location of the object are introduced by the use of a stochastic filter (Avenel et al., 2009).

## 2. Definition of a fuzzy precipitating object

A precipitating object is defined as a simple closed curve $\mathcal{C}_t$ that encompasses mesoscale precipitation patterns. The main criterion used to discriminate the nature of the precipitating object is the precipitation histogram $h$.



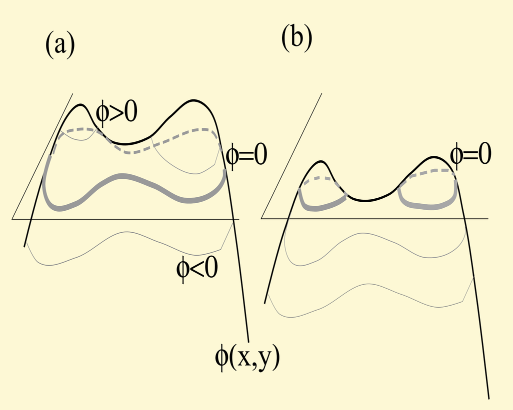
*(a): Two slightly different objects with comparable frequency histograms. (b): objet whose shape is comparable with (a) but with significant space shift. The corresponding histogram is now different from the original one with an excess of weak precipitation. (c) here two objects with close histograms but with different level of smoothness.*

The object is then described thanks to an ensemble of simple curves $\mathcal{C}_t^k$, $k \in [1, N]$ where $N$ is the size of the ensemble. The ensemble will be designed so that it discretizes the probability density function of the uncertainty related to assumptions in the tracking model. To handle a 2D contour $\mathcal{C}_t^k$, it turns out to be more convenient to consider it as an isoline of a 2D surface called a level set function.

$$\phi^k(\mathbf{x}, t) = \begin{cases} -d(\mathbf{x}, \mathcal{C}_t^k) \text{ if } \mathbf{x} \text{ is inside } \mathcal{C}_t^k \\ d(\mathbf{x}, \mathcal{C}_t^k) \text{ if } \mathbf{x} \text{ is outside } \mathcal{C}_t^k, \end{cases}.$$

where $d(\mathbf{x}, \mathcal{C}_t^k)$ is the distance between the location denoted by $\mathbf{x}$ and the closest point belonging to the contour. Then $d(\mathbf{x}, \mathcal{C}_t^k) = min_{\mathbf{x}_t(s) \in \mathcal{C}_t^k} ||\mathbf{x} - \mathbf{x}_t(s)||$ where $||.||$ stands for the L2 norm.

The object is the expected contour of the random object $\mathcal{C}_t$. It is exhibited by the zero level of the empirical ensemble mean of level set functions $\phi^k$ defined as $\bar{\phi}(\mathbf{x}, t) = \frac{1}{N} \sum_k \phi^k(\mathbf{x}, t)$.




*Evolution of the $\phi$ function during a splitting event. The heavy grey line stands for the object contour. (a): One object is present. (b) two objects appear.*

The uncertainty associated with the structure is featured by the standard deviation of the zero level, approximated at a given point $\mathbf{x}_s$ of the mean curve as the variance $v(\mathbf{x}_s) = \frac{1}{N} \sum_k \phi^k(\mathbf{x}_s, t)^2$.
The time evolution of a contour $\mathcal{C}_t$ is chosen so that it ressembles the phase propagation of a wave front. $\phi$ is the solution of an advection diffusion equation:

$$\partial_t \phi + (\mathbf{c} \cdot \mathbf{n}) |\nabla \phi| = \frac{\sigma^2}{2} \Delta \phi.$$

where $\mathbf{c}$ is a displacement vector field which is retrieved using the observed data only and $\mathbf{n}$ is the normal to the contour.

## 3. Nonlinear filtering of the contour set using particle filtering

PURPOSE: To estimate the posterior pdf $p(\mathcal{C}_q|\mathbf{y}_{1:q})$ (called the filtering distribution) of a state variable $\mathbf{x}_k$ of interest at any measurement instant $q$, given the discrete measurements series $\mathbf{y}_{1:q} = (\mathbf{y}_1, ..., \mathbf{y}_q)$ until instant $q$, and an initial distribution $p(\mathcal{C}_0)$.
1) prediction step:
The prediction uses the transition distribution $p(\mathcal{C}_q|\mathcal{C}_{r<q})$ to achieve a first approximation of the next state.
2) The correction step updates the posterior pdf using the Bayes theorem:

$$p(\mathcal{C}_q|\mathbf{y}_{1:q}) \propto p(\mathbf{y}_q|\mathcal{C}_q) p(\mathcal{C}_q|\mathbf{y}_{1:q-1})$$

An ensemble of $N$ members is used to represent the pdf:

$$p(\mathcal{C}_q|\mathbf{y}_{1:q-1}) = \frac{1}{N} \sum_{k=1}^{N} \delta(\mathcal{C}_q - \mathcal{C}_q^k)$$

where $\mathcal{C}_q^k$ is the $k^{th}$ member and $\delta$ the Dirac function. Therefore the posterior pdf is

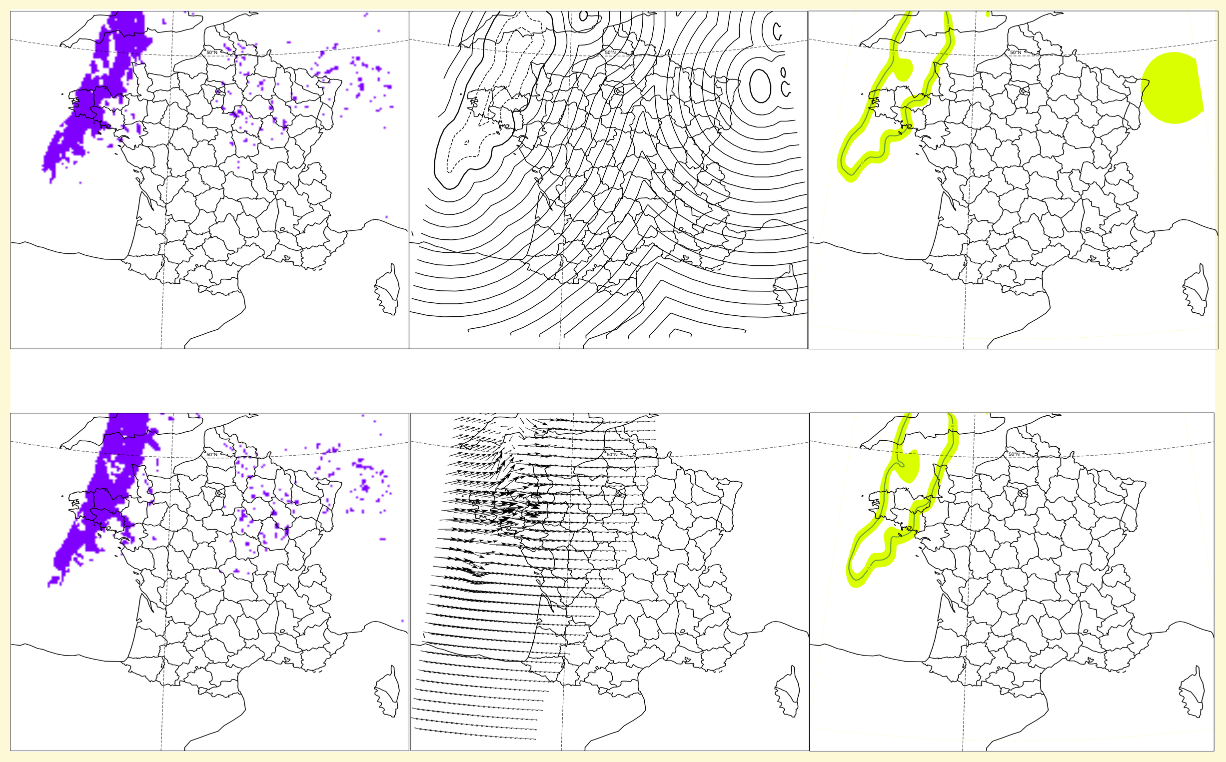
$$p(\mathcal{C}_q|\mathbf{y}_{1:q}) = \sum_{k=1}^{N} w_k \delta(\mathcal{C}_q - \mathcal{C}_q^k),$$

$$w_k = \frac{p(\mathbf{y}_q|\mathcal{C}_q^k)}{\sum_{l=1}^{N} p(\mathbf{y}_q|\mathcal{C}_q^l)}$$

is a weight applied to the $k^{th}$ member that measures the likelihood of the member by comparing its histogram to the prescribed histogram defining the object of interest.

## 4. Case study

The system is applied to the tracking of a precipitating pattern associated with a front that hits Brittany at 12UTC 29 September 2010. The first step is to initialize the object using a 12h forecast using AROME at 2.5 km of resolution. The initial contour is taken as the level 0.2 mm/h 1 hour of the precipitation field where the wavelengths smaller than 15 km are filtered out.
The filter runs with 50 contours/members. The displacement field used in the prediction step is provided by a variational optical flow method following Horn and Schunk approach.



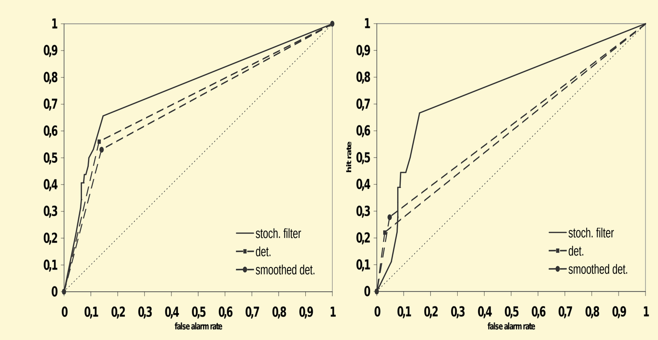
*Left column: precipitation model output at 12 UTC (top) and 13UTC (mid). Shading for precipitation in excess of 0.3 mm/h. Upper-mid panel: $\phi$ function at 12 UTC. 2nd row-mid panel: optical flow between 12 and 13 UTC. Right column: Object tracking using the digital filter method initialized at 12UTC at the initial state (top) and 1 hour further (bottom). The solid contour stands for the mean object and the shaded area for +/- 2 standard deviation of the ensemble.*

### Statistical verification

We assess in this section the ability of the stochastic filter to predict an event defined such as the precipitation exceeds a given threshold.

$$p_i = p(R > R_{tresh}) =$$
$$p(R > R_{tresh}/point \in \mathcal{S}_t) p(point \in \mathcal{S}_t) + p(R > R_{tresh}/point \notin \mathcal{S}_t) p(point \notin \mathcal{S}_t)$$

where $R$ is the precipitation, $R_{thresh}$ the threshold and $\mathcal{S}_t$ defines the interior of the object $\mathcal{C}$ at time $t$.
Hereafter it is assumed that $p(R > R_{tresh}/point \notin \mathcal{S}_t) = 0$.
We consider specifically the resolution of the probabilistic forecast through the plotting of ROC diagrams (Mason, 1982). ROC diagrams then represent the hit rates as a function of the false alarm rates for different thresholds.



*ROC curves along the time integration of the filter. The event to be detected is associated to precipitation intensity of 0.3 mm/h (left panel) or 1 mm/h (right panel). Deterministic forecast based on direct model outputs, resp. smoothed ones, are denoted by dashed lines and squares, resp. black bullets.*

## References

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## 6. Conclusions

An object-based post-processing method applied to precipitation provided by a cloud-resolving model has been developed. It is based on the particle filter approach, including precipitation histograms to characterize the patterns and stochastic laws for their evolution.
The ensemble generation technique is designed to the tracking of one single image sequence. Nevertheless the generation of an ensemble of objects using a mesoscale ensemble is straightforward.
The promising probabilistic skill of the present approach encourages to use the processed output as initialization of cost-loss models in which the economic or societal benefit can be assessed. The method is well suited to combine several deterministic models, several ensembles, or ensembles with deterministic models, the bayesian approach enabling some calibration. It may provide graphical outputs with a potential usefulness as a tool for forecasters, whereas raw data could be used in a quantitative way.