APPLICATION OF GAUSSIAN MULTI-SCALE REPRESENTATION TO FEATURE TRACKING IN METEOROLOGICAL SATELLITE IMAGERY

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Abstract

Gaussian multi-scale representation is a mathematical framework that allows to analyse images at different scales in a consistent manner, and to handle derivatives in a way deeply connected to scale. This paper uses Gaussian multi-scale representation to investigate several aspects of the derivation of atmospheric motion vectors (AMVs) from water vapour imagery. The contribution of different spatial frequencies to the tracking is studied, for a range of tracer sizes, and a number of tracer selection methods are presented and compared, using WV 6.2 images from the geostationary satellite MSG-2.

1 INTRODUCTION

Atmospheric Motion Vectors (AMVs) are estimates of atmospheric wind derived from sequences of meteorological satellite images. AMVs are routinely produced and disseminated by the main meteorological geostationary satellite data processing centres around the world. They play a key role in the monitoring of the Earth's atmosphere, as they provide information on atmospheric wind over regions, such as oceans or deserts, that are not well covered by the network of conventional meteorological observations. There is an ever increasing demand, by the user community, on the quality of AMVs, and therefore there is a requirement for the continuous advancement of derivation methods (Velden et al., 2005).

Most operational derivation schemes consist of similar steps: tracer selection, tracking, height assignment and quality control (Velden et al., 1997; Schmetz et al. 1993). First, suitable tracers (typically small square windows) are selected from the first image of a sequence, and an apparent motion vector field is obtained by tracking these tracers across images. Usually a template matching method is used for tracking: the best match for each tracer, according to a suitable similarity function, is located within a search area in the second image. From the resulting motion vectors (MVs), knowing the geographical coordinates associated with each pixel of the image, it is possible to obtain AMVs, i.e. estimates of atmospheric wind.

AMVs can be derived from visible or infrared spectral bands. In principle, any elements whose change, during the time interval between consecutive images, are mainly due to horizontal wind, can be used to derive AMVs. In WV imagery, the elements that can be tracked are high-level clouds and upper-tropospheric water vapour features. Water vapour (WV) images have a smooth appearance, with low local contrast, and WV imagery poses its own challenges to the derivation of AMVs (Buche et al., 2006).

Tracer selection is usually the first step in the derivation of AMVs. Not all tracers lead to good estimates of wind, and suitable criteria allowing an a priori selection of promising tracers may contribute to a better overall quality of the motion field and to a better use of the available computing resources. In the IR 10.8 µm imagery, often strong gradients are sought, as they allow the detection of well defined cloud edges. However, the nature of WV imagery is different (e.g. there are no sharp edges); operational derivation schemes typically include a tracer selection step that preferably selects tracers with a high standard deviation and strong gradients (Holmlund, 2002; Velden et al., 1997).
The contribution of different spatial frequencies to the tracking is another interesting aspect to explore. Apart from instrumental noise, small scale non-advective atmospheric disturbances may effectively play the role of noise in AMV derivation, and it would be interesting to know how the quality of the motion field is affected, particularly in connection with tracer size.

Gaussian multi-scale representation (Lindeberg, 1994) is a mathematical framework that allows to analyse images at different scales in a consistent manner, and to handle derivatives in a way deeply connected to scale. This framework underpins some very successful techniques, e.g. SURF (Bay et al., 2009) developed by the computer vision community for tracking motion of quasi-rigid bodies.

This paper uses Gaussian multi-scale representation to investigate several aspects of the derivation of AMVs from water vapour imagery. Section 2 briefly introduces Gaussian multi-scale representation. Section 3 studies the contribution of different frequencies to the tracking, for a number of tracer sizes, section 4 presents and compares several tracer selection methods, and section 5 concludes the paper.

2 GAUSSIAN MULTI-SCALE REPRESENTATION

In Gaussian multi-scale representation (Lindeberg, 1994) an image $I(x, y)$ is embedded in a family of convolutions with the 2-dimensional Gaussian kernel $G$:

$$L(x, y; \sigma) = G(x, y; \sigma) * I(x, y) \quad (\sigma \in \mathbb{R}^+)$$

where

$$G(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2 + y^2}{2\sigma^2}} \quad (x, y \in \mathbb{R})$$

Each $L(x, y; \sigma)$ can be seen as a smoothed version of the original image $I(x, y)$ (see figure 1) and the original image $I$ is the member of the family for $\sigma = 0$. In equation (1), semicolon has been used as separator to stress the different roles of $\sigma$ and the spatial variables.

The Gaussian function is a regularizing kernel with many useful properties, extensively discussed in the literature by e.g. Lindeberg (1994), Florack et al. (1992) and Marr and Hildreth (1980). In particular, it provides an optimal compromise between space localization and frequency localization (Marr and Hildreth, 1980), and convolution with a Gaussian kernel does not introduce spurious structures (Lindeberg, 1994).

The properties of the Gaussian kernel make Gaussian multi-scale representation a sound and efficient framework to analyse images. It can be used to study the contribution of different frequencies, and it also provides a natural and efficient way of calculating derivatives in a generalized sense. Note that it does not really make sense to talk about the partial derivatives of $I$ in the traditional sense, as $I$ might not even be continuous. However, when $I$ is seen as embedded in a family of convolutions with the 2-D Gaussian kernel, as described in equation (1), it is possible to consider the partial derivatives, in a generalized sense:

$$D_x I(x, y; \sigma) = \frac{\partial G}{\partial x}(x, y; \sigma) * I(x, y)$$

and

$$D_y I(x, y; \sigma) = \frac{\partial G}{\partial y}(x, y; \sigma) * I(x, y)$$

A simple calculation gives:

$$\frac{\partial G}{\partial x}(x, y, \sigma) = -\frac{x}{\sigma^2} G(x, y, \sigma) \quad \text{and} \quad \frac{\partial G}{\partial y}(x, y, \sigma) = -\frac{y}{\sigma^2} G(x, y, \sigma)$$

which allows the efficient computation of $D_x I(x, y; \sigma)$ and $D_y I(x, y; \sigma)$. Note that the derivatives of $I$ are necessarily linked to a particular value of $\sigma$, i.e. to a scale (see figure 2) and that derivatives for $\sigma = 0$ (i.e. the original image) are not defined.
Figure 1: The left panel shows, from top to bottom, an original MSG-2 IR 10.8 image and two Gaussian blurs (for $\sigma = 2$ and 8). The right panel shows the same, for the MSG-2 WV 6.2 image at the same date and time. The middle panel shows the Gaussian filters used for the convolutions.

Figure 2: Partial derivatives $D_x L(x, y, \sigma)$ of the original images shown in figure 1 for $\sigma = 3$. Left: IR 10.8, right WV 6.2.
3 SPATIAL FREQUENCIES

This section studies the contributions of different spatial frequencies to the tracking, using the framework introduced in the previous section. Each Gaussian blur $L(x, y, \sigma)$, produced by the convolution of the original image $I(x, y)$ with the 2-dimensional Gaussian kernel, as described in equation (1), is essentially a smoothed version of the original image from which the higher spatial frequencies have been removed, i.e. a Gaussian blur is a low-pass filter.

The data used in this study were brightness temperatures from the MSG-2 water vapour 6.2 $\mu$m channel. The geographical area (south-western Europe and North Africa) can be seen in the upper left panel of figure 1. The dataset consisted of a set of 10 image sequences, one for each day of the period 10-19 July 2007. Each sequence consisted of three images, with a time interval of 15 minutes between them, and the time of the central image was approximately 12 UTC. From the original images, sets of Gaussian blurs were derived for several values of $\sigma$: 0 (i.e. originals), 0.5, 1, 1.5, 2, 2.5, 3, 4, 5, 6, and 7.

A range of tracer sizes was explored: 20x20, 24x24, 28x28, 32x32 and 36x36. Concerning the tracking, a search area of 30 pixels around tracer boxes was used, and Euclidean distance between brightness temperatures was used as similarity function. In this experiment, no attempt was made to select tracers, and to generate the sample, a selection grid with 12 pixels between grid points in both directions was used. Each tracer box in the central image of the triplet, $I_t$, was tracked in the final image $I_f$ to produce the AMV $(u_2, v_2)$, and in the initial image $I_0$, to produce the AMV $(u_0, v_0)$. The final AMV $(u_1, v_1)$ was the mean of $(u_0, v_0)$ and $(u_2, v_2)$.

To evaluate results, a quality index was used, composed of three terms, equally weighted: spatial consistency between neighbour AMVs; temporal downstream consistency between vectors $(u_0, v_0)$ and $(u_2, v_2)$, obtained respectively from the first and middle, and from the middle and last images in the sequence; and consistency with the level of best fit of a wind profile obtained from interpolation from a numerical weather prediction (NWP) wind field (a 12-h forecast from the ERA-Interim dataset).

Results are shown in figure 3. The number of AMVs in the sample varies from 37584 for $\sigma = 0$ and tracer size 20x20 to 33914 for $\sigma = 7$ and tracer size 36x36; displacements $v = 0$ (less than 10%) were not included in the sample.

![Figure 3: Curves showing the relation of the quality index to $\sigma$ for a range of tracer sizes.](image-url)
Each line in the plot is associated to a tracer size. A consistent improvement, as tracer size increases, can be seen for all the values of $\sigma$ tested. The values obtained for 20x20 are well below the rest of tracer sizes, and suggest that it is a too small size to produce good quality AMVs. For all the tracer sizes tested, the curve describing the relation of QI to $\sigma$ shows the same pattern: QI increases from $\sigma = 0$ to around $\sigma = 1$ and then decreases slowly. These results suggest that the highest frequencies have a negative impact on the tracking. It is not clear whether this is due to small-scale non-advective atmospheric disturbances or to instrumental noise. Further research could study their relative contributions.

4 TRACER SELECTION

The purpose of the study described in this section was to compare the performance of different methods to select locations of interest. As mentioned in section 1, not all tracers lead to good estimates of wind, and suitable criteria for selecting promising tracers contributes to an overall improvement of the resulting motion field and to a better use of the available computational resources.

The dataset used in this experiment was the same as that described in the previous section. A Gaussian filter ($\sigma = 1$) was applied to all the images in the dataset, and the tracer size used was 24x24. The search area and the similarity function used were also as in the previous study. To generate the sample, a selection grid with 48 pixels between grid points in both directions was used. Within each 48x48 domain, a 24x24 tracer was selected, according to each of the methods described below. Temporal downstream consistency and consistency with an NWP 12-h forecast from ERA-Interim (level of best fit) were used for evaluation. Spatial consistency was not used in this study, as tracers were quite distant: 48 pixels on average, in each direction, compared with 12 pixels in the previous study.

The following methods to select tracers were compared in this experiment:

- **A control selector** was used as reference: the tracer is located in the centre of the tracer domain.
- **Maximum contrast**: from each tracer domain, the tracer that maximizes contrast is selected.
- **Maximum standard deviation**: from each tracer domain, the tracer that maximizes standard deviation is selected.
- **Maximum gradient modulus**: The tracer is centred on the location that maximizes the gradient modulus.
- **Maximum Hessian**. The tracer is centred on the location that maximizes the determinant of the Hessian matrix

$$
\mathcal{H}(x, y, \sigma) = \begin{bmatrix}
L_{xx}(x, y, \sigma) & L_{xy}(x, y, \sigma) \\
L_{yx}(x, y, \sigma) & L_{yy}(x, y, \sigma)
\end{bmatrix}
$$

for \((x, y) \in I_1, \sigma = 1\) (6)

Derivative were calculated as described in section 2. Maximizing standard deviation, contrast or the gradient modulus are standard techniques for tracer selection in the derivation of AMVs. The maximum of the determinant of the Hessian matrix to detect locations of interest has been used by several researchers in motion tracking of quasi-rigid bodies, to detect blob-like structures (Lindeberg, 1994; Bay et al., 2008). Although motion tracking in geophysical fluids is essentially different from motion tracking of quasi-rigid bodies, it is, in principle, a detector worth considering.

The results of the comparison are shown in figure 4. The number of AMVs in the sample (displacements $v = 0$ not included) was 1840 for the control case, and a similar number for the other detectors. As this study tested only one value of $\sigma$ and one tracer size, it was possible to present results in a more detailed way than in the previous study. Figure 4 shows the distribution of relative frequencies for ten equally-spaced bins. Considering that the main uses of AMVs are NWP data assimilation and nowcasting, it is clear that a high percentage of high-quality AMVs is more valuable than a high mean quality. Table 1 summarizes the results and shows the relative frequency of AMVs with a consistency index $CI \geq 80$. 

Figure 4: Relative frequencies of consistency indices intervals for each tracer detector tested. Left: downstream temporal consistency. Right: consistency with NWP wind fields. Notice that the control detector appears in all panels, to facilitate the comparison.

Table 1: Relative frequency (%) of AMVs with $CI \geq 80$, for each tracer selection method.
All the detectors tested showed a clear improvement with respect to the control, for both indices, and the maximum gradient modulus showed the best overall performance. It is important to notice that these detectors have been applied to the smoothed version \((\sigma = 1)\) of the middle image \(I_1\), not to the original image. The detector based on contrast, being very simple, showed a performance comparable or better than the maximum determinant of the Hessian. The dataset covers a small geographical area and a small time period, and a more comprehensive study should cover a longer period of time, a larger geographical area, and perhaps other detectors.

5 CONCLUSION

This paper has presented recent research, underpinned by Gaussian multi-scale representation, related to tracer selection and motion tracking in the context of AMV derivation from WV imagery. First, it has described a study on the contribution of different spatial frequencies to the tracking, for a range of tracer sizes. The main finding is that the higher frequencies might actually have a negative impact on the tracking. Further research could help understand to which extent this observed negative impact is linked to small scale non-advective atmospheric disturbances.

A second study, describing a number of methods for tracer selection and comparing their performance, has been presented. While all the detectors show a clear improvement with respect to the control, the maximum gradient modulus seems to be slightly better than the rest for the area and period tested. Both studies could be extended to the whole area covered by MSG-2, and to a longer period of time.

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REFERENCES


