Multiscale Image Processing Methods

Jason P. Byrne[1], C. Alex Young[2], Peter T. Gallagher[1], R. T. James McAteer[3], David M. Long[1]

[1] Astrophysics Research Group, School of Physics, Trinity College Dublin, Dublin 2, Ireland

[2] ADNET Systems Inc., NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA

[3] Catholic University of America, NASA Goddard Space Flight Center, Greenbelt, MD 20771, USA

1. Abstract

Image processing plays an important role in the analysis of spacecraft data. With the large volumes of information currently available from missions such as Hinode and STEREO, our aim is to produce computationally fast methods for extracting features of interest (loops, filaments, waves and eruptions).

Solar structures appear on a variety of scales, from large coronal mass ejections (CMEs) to smaller, more detailed, loop systems. Multiscale image processing methods enable us to study these features as a function of scale[1]. Here we use these methods to study the multiscale properties of a CME front observed by SOHO/LASCO and STEREO.

2. Background & Motivation

Processing of images is important to obtain the structures in the data. The viewing of different scales on a data set is a natural step since it is quite conceivable that certain structures may not be easily discernible depending on the scale size in view. Noise also has an inherent scale dependence and thus multiscale decompositions are useful for denoising an image.

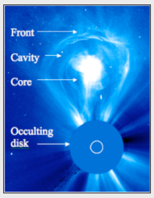

Fig. 1: CME features with different scales.

In a CME we note the different structures (Figure 1) which our multiscale analysis will show to occur on particular scales. We use the scale dependence to detect the front edge and characterise it with an ellipse, to study kinematics[2] and compare with theory[3,4].

3. Multiscale Edge Detection

We explore a method of multiscale decomposition on an image through the use of ***high and low pass filters***, producing details and approximations respectively5,[6]. Here, the low pass filter is a normal distribution and the high pass filter is a DoG: Derivative-of-Gaussian[7] (Figure 2).

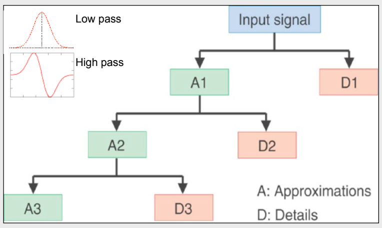

Fig. 2: *Convolving the image with high and low pass filters yields details at each level for N levels of decomposition.*

- The image is convolved with low (approximation) and high (detail) pass filters (Figure 2)
- The smoothed first approx. A1 is then convolved again to give A2 and D2.
- This is repeated to give N scales of decomposition.
- Figure 3 illustrates (in 1D) the convolution of the high pass DoG filter, and its effectiveness in detecting edges.

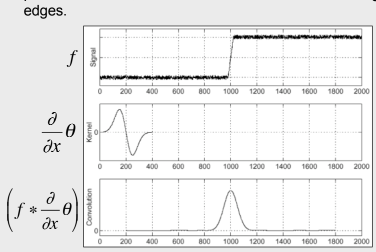

Fig. 3: *The convolution of a DoG to identify an edge in a 1D signal.*

Figure 4, below, shows the results for a Lasco/C2 image which has been successively convolved with our high and low pass filters. We can see in the structure of the CME that different levels of detail present themselves at different scales.

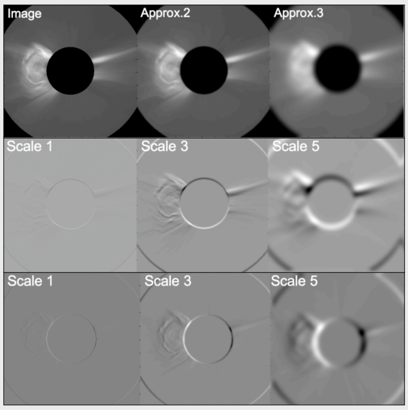

Fig. 4: *The horizontal (middle) and vertical (bottom) details of scales 1, 3, and 5 for decompositions of a Lasco/C2 image (top) of a CME on 24-Jan-07.*

Akin to a ***Canny edge detector***[8]***,*** the horizontal & vertical coefficients resulting from our high pass filtering are combined to form the gradient space, given by:

$$\nabla f(x,y) = \left[\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}\right]$$

The gradient information has an ***angular component***:

$$\alpha = \tan^{-1}\left(\frac{\partial f}{\partial y} \Big/ \frac{\partial f}{\partial x}\right)$$

And the ***edge strength*** is the magnitude of the gradient:

$$\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2}$$

4. Multiscale Edge Characterisation

Non-Maxima Suppression:

The angular component of the gradient specifies its direction which always points across the greatest intensity change (an edge). Thus the gradient information is utilised in a method of ***pixel chaining*** (Figure 5) by the following steps:

1) A pixel in the gradient space is chosen (e.g. a local maxima).

2) The information on the nearest neighbour pixels is extracted.

3) Thresholding with regard to gradient direction chains pixels along maxima, highlighting edges and suppressing the rest of the data.

Determining edges in this way has benefits over previous 'point & click' methods which can be misleading due to the subjective nature of users specifying edges by eye.

A characterisation of the edges gives a model which can be consistently applied to a time series of solar data; e.g. an expanding ellipse to model the propagation of a CME or EIT wave.

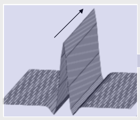
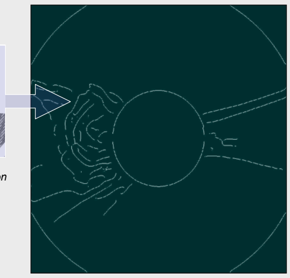

Fig. 5: *Graphical illustration of the non-maxima suppression for a CME observed by LASCO/C2. Pixels are chosen along maxima and chained accordingly, to give the edges displayed here in a binary mask.*

Ellipse Fitting:

A model such as an ellipse has the benefit of providing the ***kinematics and morphology*** of a moving structure (Figure 6).

Kinematical analysis includes height-time profiles, velocities and accelerations.

Changing morphology of the ellipse provides the inclination angle, major/minor axes, angular width, and radius of curvature.

Measuring these properties in the observed data (Figure 7) is important for comparing to theoretical models.

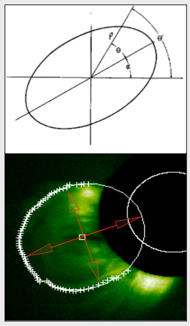

Fig. 6: *The inclined ellipse (top) and ellipse fit (bottom) applied to a CME front seen in SECCHI/A onboard STEREO.*

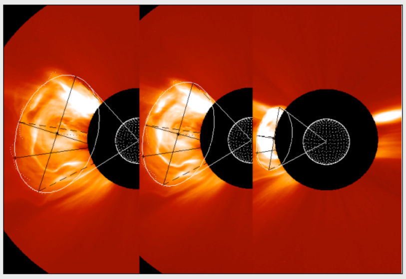

Fig. 7: *Propagation and ellipse fit of a CME observed by LASCO/C2 on 24-Jan-07.*

5. Future Directions

The ***application of multiscale methods to Hinode data*** (Figure 8) can highlight structure on scales not immediately obvious in images. Fine details in flares, waves and other solar phenomenon can be better emphasised by WTMM and edge detection processes.

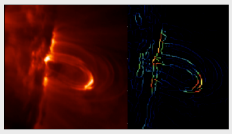

Fig. 8: *A post flare loop observed with EIS and edges of the loop determined using WTMM.*

Multiscale analysis will be explored further; there are many ***other multiscale transforms*** that may be better suited for solar data, e.g. anisotropic wavelets and curvelets.

Our methods have been designed with ***automated edge detections*** and characterisations in mind[9]. Automation is necessary for today's large data volume and for space weather forecasting.

6. References

1. McAteer, R. T. J., Young, C. A., Ireland, J., Gallagher, P. T., Byrne, J. P. 2007, Sol. Phys., *submitted*
2. Gallagher, P. T., Lawrence, G. R. & Dennis, B. R., 2003, ApJ, 588, L53
3. Krall, J., Chen, J., & Santoro, R., 2000, ApJ, 539, 964
4. Forbes, T. G. & Priest, E. R., 1995, ApJ., 446, 377
5. Stenborg, G. & Cobelli, P. J., 2003, A&A, 398, 1185
6. Young, C. A. & Gallagher, P. T., 2007, Sol. Phys., *submitted*
7. Starck, J. L. and Murtagh, F., Astronomical Image and Data Analysis, Springer, 2002.
8. Gonzalez, R.C. & Woods, R.E., Digital Image Processing: Second Ed. (Prentice-Hall).
9. Robbrecht, E. & Berghmans, D., 2004, A&A, 425, 1097

JPB's work is supported by NASA's Living with a Star Program and Science Foundation Ireland's Research Frontiers Programme. DML is supported by the Irish Research Council for Science, Engineering & Technology.