15.14: Motion Estimator Based On Hierarchical Clusters

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Abstract

In this paper, we describe the use of statistically derived hierarchical clusters of weather data to derive movement estimates from pairs of frames in a time sequence. We show that the use of hierarchical clusters enables small cells to be tracked over short periods of time while using the movement of the larger scale features they are embedded in for longer periods.

The motion estimator has been applied both to reflectivity data obtained from the National Weather Service Radar (WSR-88D) and to cloud-top infrared temperatures obtained from the GOES-11 satellite. We demonstrate the results on both these sensors.

1. Short-term forecast methods

The operational way of identifying storms from radar images involves the use of multiple thresholds and counting runs of values above a threshold along a radial. The centroids are then used as proxy for the storms (Johnson et al. 1998) and tracked either on the basis of proximity to expected position or through a a linear programming approach (Dixon 1994). Change in position is extrapolated.

A second technique is to use rectangular sub-grids and find the maximum correlation within a search radius (Rinehart and Garvey 1978; Tuttle and Gall 1999). A modification of this technique is to pre-filter the data so as to track only the larger scales (Wolfson et al. 1999; Lakshmanan 2000). It is also possible to use sub-grids ranging in size from that of the entire image to small 16km x 16km grids and to compute motion estimates at each of these scales. Smoothness criteria can be used to constrain these estimates at different scales.

Identifying, matching and extrapolating storm core locations is suitable for small scale storms. The large scale features and cross-correlation technique is suitable for longer forecasts, but with loss of detailed motion estimates. An assumption here is that the storms are of the scale of the sub-grid, not larger. The multiscale estimation is suitable also for large scale forecasts, but with less precise detailed motion estimates.

When used for advection, all the correlation techniques rely on reverse projection, so there needs to be wind speed at the spot where the storm is moving to. The image template methods also assume that all pixels within a grid are moving together.

We use a hybrid approach where motion estimates are made for groups of storms (rather than for sub-grids of the image), but at various scales. The motion estimate for a storm cell is the movement that minimizes the mean-absolute-error between the current frame and corresponding pixels in the previous frame, except that the template is not a sub-grid of the image, but is instead the actual shape of the storm cell.

Instead of simply matching storm cells across frames, motion estimates are made by finding the best match for the storm-template. Thus, the major steps in the technique are:

1. Find storms at different scales.

2. Estimate motion at the various scales.

3. Forecast for different periods using motion at different scales.

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2. Identifying storms

A K-Means clustering technique from Lakshmanan (2001); Lakshmanan et al. (2002) is used to identify components in vector fields. The technique provides nested partitions, i.e. the identified storms structures are strictly hierarchical. The technique works by clustering image values (reflectivity/infrared temperature, etc.) in the neighborhood of a pixel on two opposing criteria:

- Belong to same cluster as your neighbors.
- Belong to cluster whose mean is closest to your value.

Hierarchical segmentation is incorporated into the K-Means clustering technique by steadily relaxing inter-cluster distances.

K of this K-Means clustering is not the number of regions in the final segmented output. It is the number of central vectors about which we do the clustering. The number of regions is determined by the spatial location. As the number K increases, the clusters cover a smaller range in the texture space. In case the number of regions is not known a priori, a very high value of K may be chosen. The most detailed segmentation may have too many regions, but coarser levels might yield the desired result. This is one advantage of using a hierarchical technique.

We iteratively move pixels minimizing

$$E(k) = \lambda d_m(k) + (1-\lambda) d_c(k) \qquad 0 \leq \lambda \leq 1 \tag{1}$$

where the distance in the measurement space is:

$$d_m(k) = \parallel \mu_k^n - T_{xy} \parallel \tag{2}$$

and the discontiguity measure is::

$$d_c(k) = \sum_{ij \epsilon N_{xy}} (1 - \delta(S_{ij}^n - k)) \tag{3}$$

A region growing algorithm is employed to build a set of connected regions, where each region consists of 8-connected pixels that belong to the same K-Means cluster. If a connected region is too small, then its cluster mean (the mean of the texture vectors at each pixel in the region) is compared to the cluster means of the adjoining regions and the small region is merged with the closest mean. The result of the K-Means segmentation, region growing and region merge steps is the most detailed segmentation of the image.

The inter-cluster distances of all adjacent clusters (or regions) in the image are computed. A threshold is set such that half the pairs fall below this threshold. If a pair of clusters differs by less than this threshold, the clusters are merged and cluster means updated. This process is continued until no two adjacent regions are closer in cluster space than the threshold. When this process is complete, we have the next coarser scale of the segmentation. This process is repeated until no changes happen.

3. Motion Estimation

Once the storms have been identified from the images, these storms are used as a template and the movement that minimizes the absolute-error between two frames is computed. For radar images, we used consecutive (5 min) volume scans. For satellite imagery, we used frames 400 seconds apart.

Motion estimation is done by moving a template of the identified cluster at the appropriate scale around in the previous image. A matrix of mean absolute error at the different positions is obtained as shown in Figure 1

The field is minimized by weighting each pixel by how much it differs from the absolute minimum and finding the centroid.

For each storm template, we also get a growth/decay estimate. This is based on how much the average value inside the template changes based on the template at the best match.

4. Short-term Forecast

The forecast of the fields is done based on the motion estimates, growth and decay heuristic and the current data. Forecasts can be made on fields other than the tracked field. For example, motion estimates can be derived from VIL and applied to radar reflectivity and probability fields of lightning and hail.

The forecast is done in three steps:

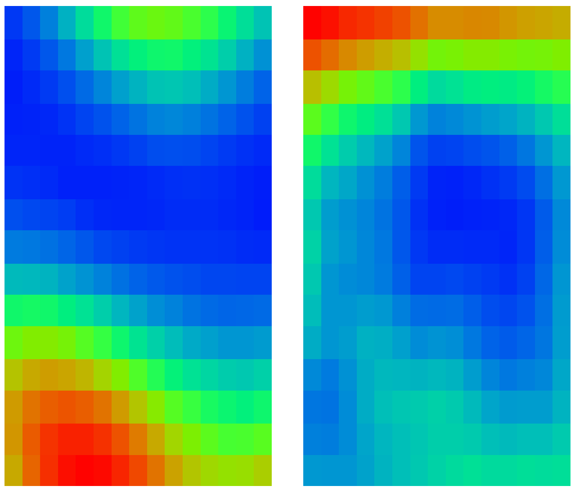

Figure 1: Matrix of mean absolute error by position. Larger errors are "hotter". Two different locations are shown.

1. Forward: project data forward in time to a spatial location given by the motion estimate at their current location and the elapsed time.

2. Define a background (global) motion estimate given by the mean storm motion.

3. Reverse: obtain data at a spatial point in the future based on the current wind direction at that spot and current spatial distribution of data.

The skill of this technique is quantititavely measured by comparing, for example, the 30 minute forecast against the actual field closest to 30 minutes ahead. Results over a 750 minute period on reflectivity from the Fort Worth radar on April 1, 1995 are shown in Figures 2 and 3.

The CSI seems to indicate the technique performs a lot better than persistence. The MAE, especially in the longer-range forecasts, doesn't show much difference between the two. The reason is that the MAE takes into account actual reflectivity values. We are good at predicting storm location, but not so good at growth/decay.

A forecast based on satellite infrared temperature is shown in Figure 4.

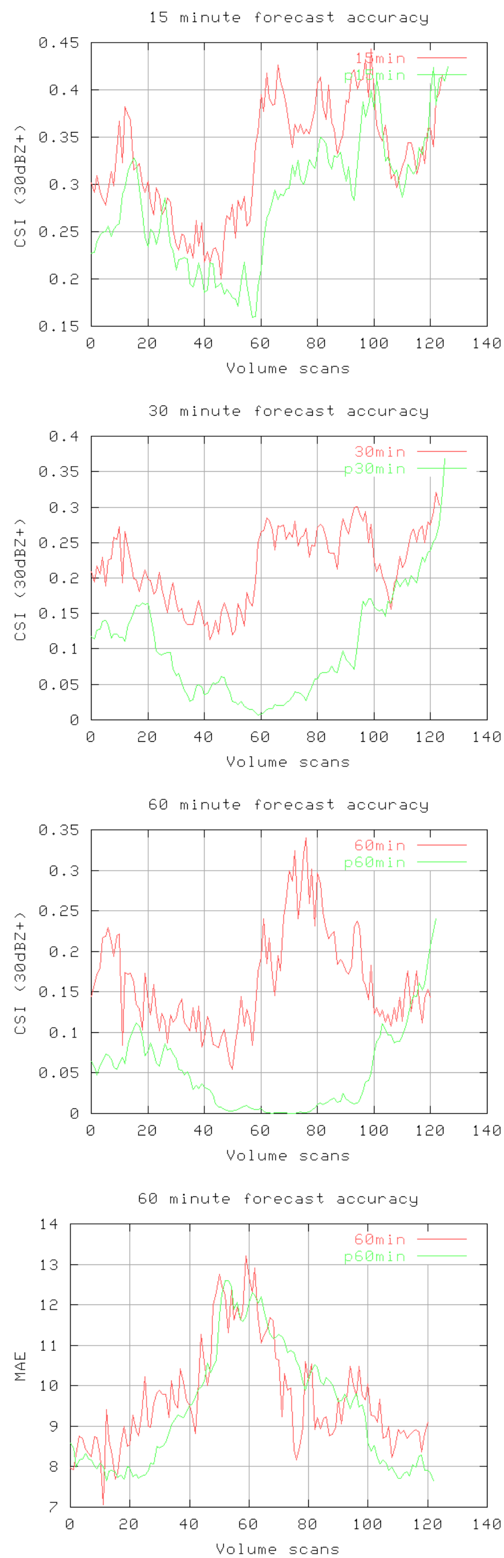

Figure 2: Skill (red) at forecasting a radar reflectivity field compared to a persistence forecast (green). (a) Values 30dBZ and above for 15 minutes (b) Values 30dBZ and above for 30 minutes (c) Values 30dBZ and above for 60 minutes (d) Mean absolute error in 60 minute forecast

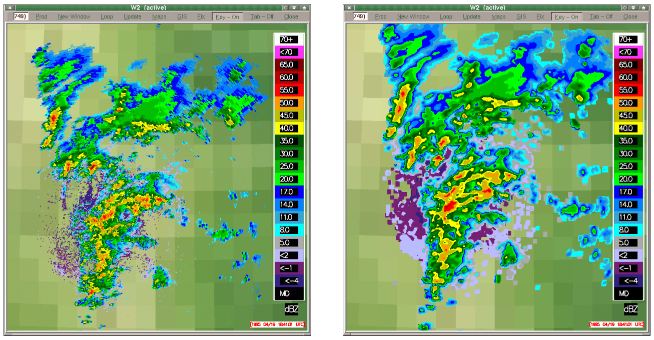

Figure 3: The original (left) and a 15 minute forecast on KFWS reflectivity data from April 1995.

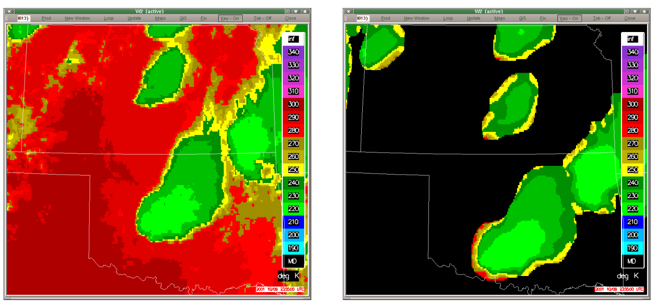

Figure 4: The original (left) and a 30 minute forecast of infrared temperature from Oct. 1999.

Further work is needed in these areas:

1. High bias – associated with splatting during forward projection.
2. Poor forecast of actual data values (high MAE), i.e. poor growth/decay estimate.
3. A better choice of scale for making forecasts.
4. Assimilation of mesoscale model wind speeds.
5. Use of Doppler radar velocity estimates.
6. Images look unrealistic beyond 60 minutes.

5. Acknowledgements

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