Nowcasting of Thunderstorms from GOES Infrared and Visible Imagery

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Abstract

In this paper, we describe our progress in identifying and tracking storms at multiple scales from satellite infrared (11-micron Band 4) and visible (Band 1) channels. Storms are identified by clustering the pixels in the input images using spatial-contiguity-enhanced K-means clustering. Identified clusters are then processed morphologically to yield self-consistent storms.

Identified storms (at all the scales) are tracked using a hybrid scheme that minimizes mean absolute error between frames of the input sequence of images and then smoothed temporally using Kalman filtering. This yields a grid of motion vectors at each pixel in the spatial domain.

The motion vector estimated from the sequence is used to nowcast the images. Comparison of the nowcasts with the observed values at the corresponding time gives a measure of skill of the nowcast.

Statistical properties are extracted for each cluster. The extracted properties are used as inputs to an automated decision tree training algorithm to identify regions of overshooting tops.

Results and measures of skill are demonstrated on a sequence of images from Oct. 12-13, 2001.

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1. Short-term forecast methods

There are two broad techniques to ”track” storms from remotely sensed imagery. One method is to identify the centroids of spatially-contiguous pixels above a particular threshold and to match these centroids across time. A principed approach to such association can use linear programming (Dixon 1994), although most implementations use heuristics based on proximity and size of the storms in question. Change in position and trends of storm properties are then 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.

2. Identifying storms

A K-Means clustering technique from Lakshmanan et al. (2003) 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

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

where the distance in the measurement space is:

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

and the discontiguity measure is::

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

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. At each stage of the hierarchical segmentation, a distance threshold equal to the average inter-cluster distance of the remaining threshold is used. A user-defined size threshold is also used. If a cluster is smaller than the size threshold, then it is combined with the closest cluster provided it is within the distance threshold. If no nearby cluster exists, the cluster that doesn't meet the size criterion is retained as an individual storm at this scale. When the clusters are merged, the cluster means updated. This process is continued until no two adjacent regions are closer in cluster space than the distance threshold and no regions smaller than the size threshold are left. When this process is complete, we have the next coarser scale of the segmentation. This process is repeated until no changes happen.

We carried out this K-means segmentation process on the infrared (11-micron) channel using $K = 4$ and

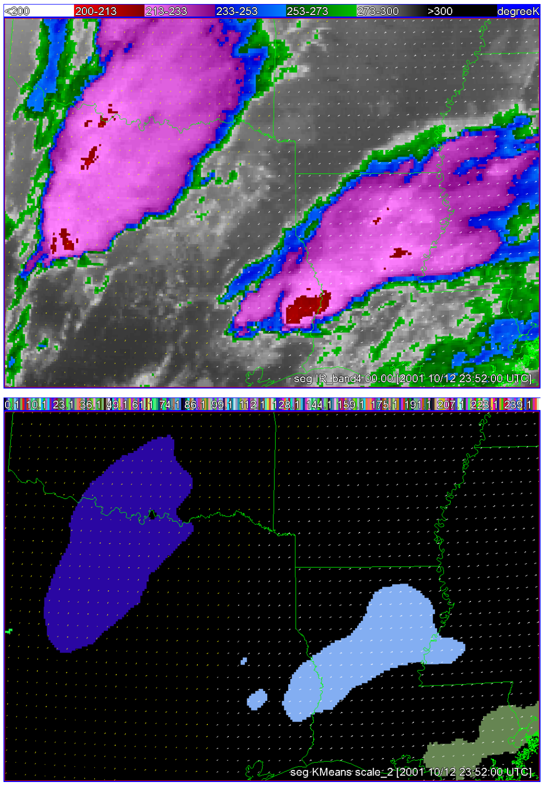

Figure 1: (a) Infrared image (b) Coarsest scale of segmentation

size thresholds of 50, 200 and 500 pixels (where each pixel is approximately $4km x 4km$). Since we are interested in forecast intervals on the order of hours, only the largest scale of segmentation is used. Example results are shown in Figure 1.

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 satellite imagery, we used frames 60 minutes apart. This time scale was chosen because we wished to create forecasts of the images at hourly intervals.

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 2

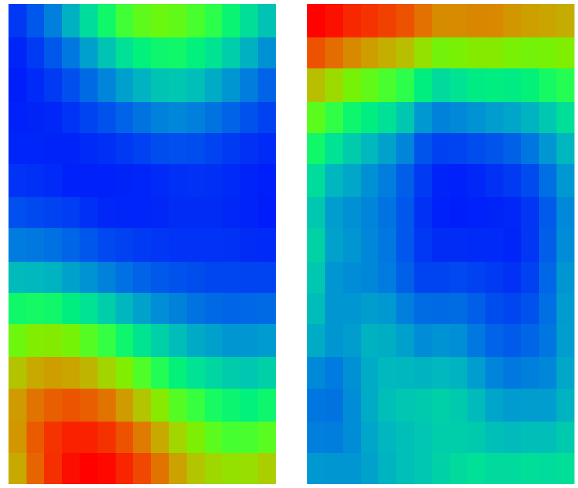

Figure 2: Matrix of mean absolute error by position. Larger errors are "hotter". Two different locations are shown.

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

The procedure gives a motion estimate in areas where there are storms. In between storms, the wind vectors are interpolated spatially, so as to yield a smooth, continuous windfield.

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 were derived from the infrared channel and applied to both the IR and visible channels.

The forecast is done in three steps:

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

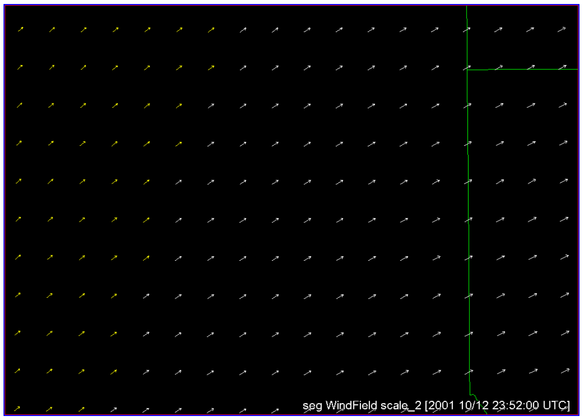

Figure 3: Detail of windfield extracted from matching template.

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.

Example forecast images are shown in Figures 4 and 5. It is apparent that the varying intensity levels in visible imagery poses a problem – an albedo-type image needs to be used in the future.

The skill of this technique is quantititavely measured by comparing, for example, the 60 minute forecast against the actual field closest to 60 minutes ahead. Results over a 48-hour period on both IR and visible channels, as compared to a persistence forecast, are shown in Figure 6. As can be observed from the figures, the advection forecast does poorly when storms are evolving (first half of the sequence), but beats persistence when the storms are organized (second half of the sequence). Also, the IR forecasts are skilful, but the visible channel forecasts are not.

5. Acknowledgements

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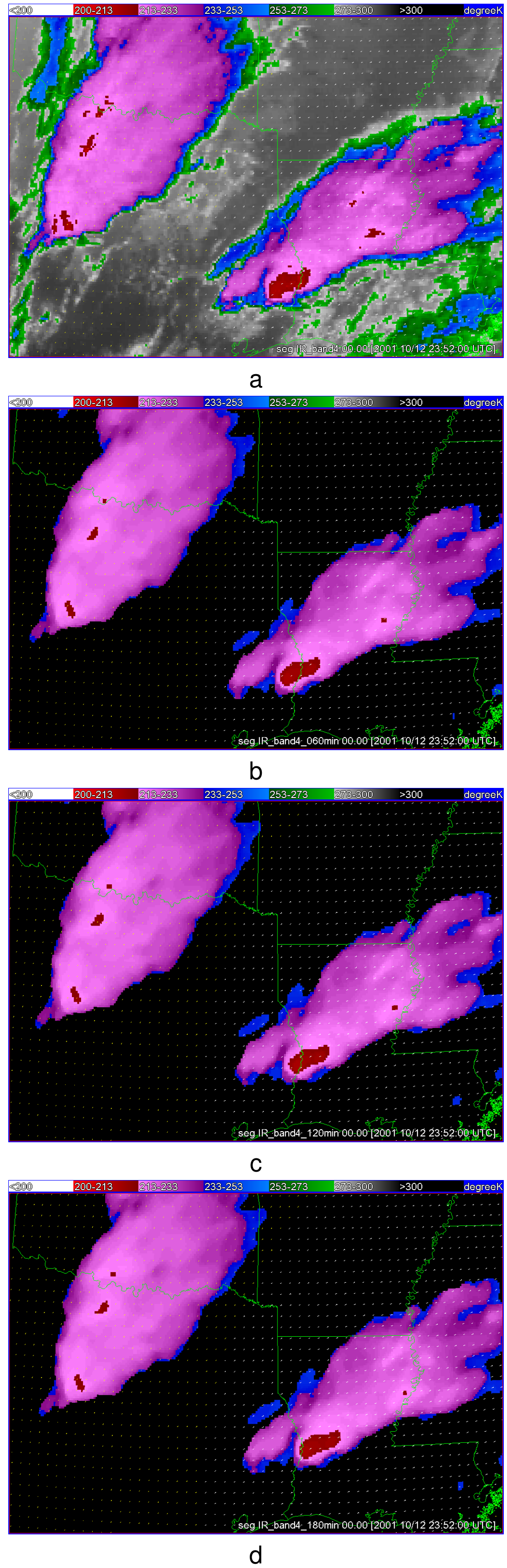
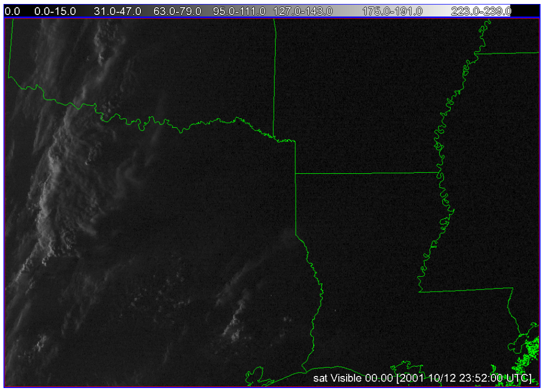
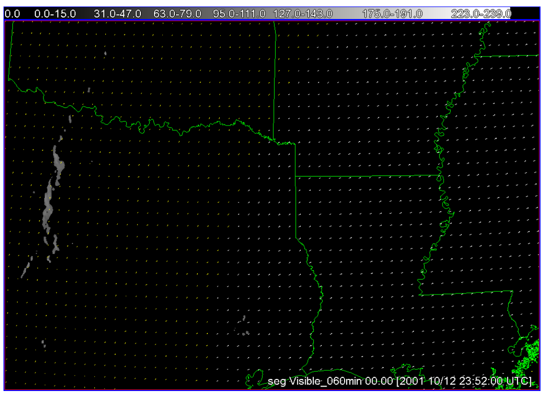


Figure 4: (a) Infrared Image (b) 1-hour forecast (c) 2-hour forecast (d) 3-hr forecast



a



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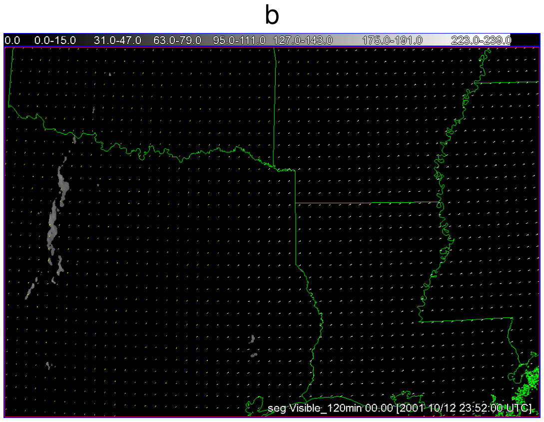

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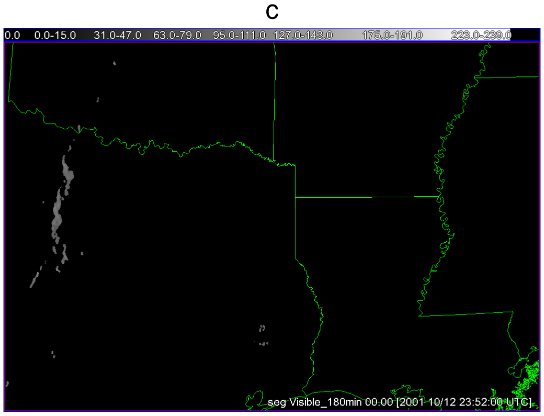

d

Figure 5: (a) Visible Image (b) 1-hour forecast (c) 2-hour forecast (d) 3-hr forecast

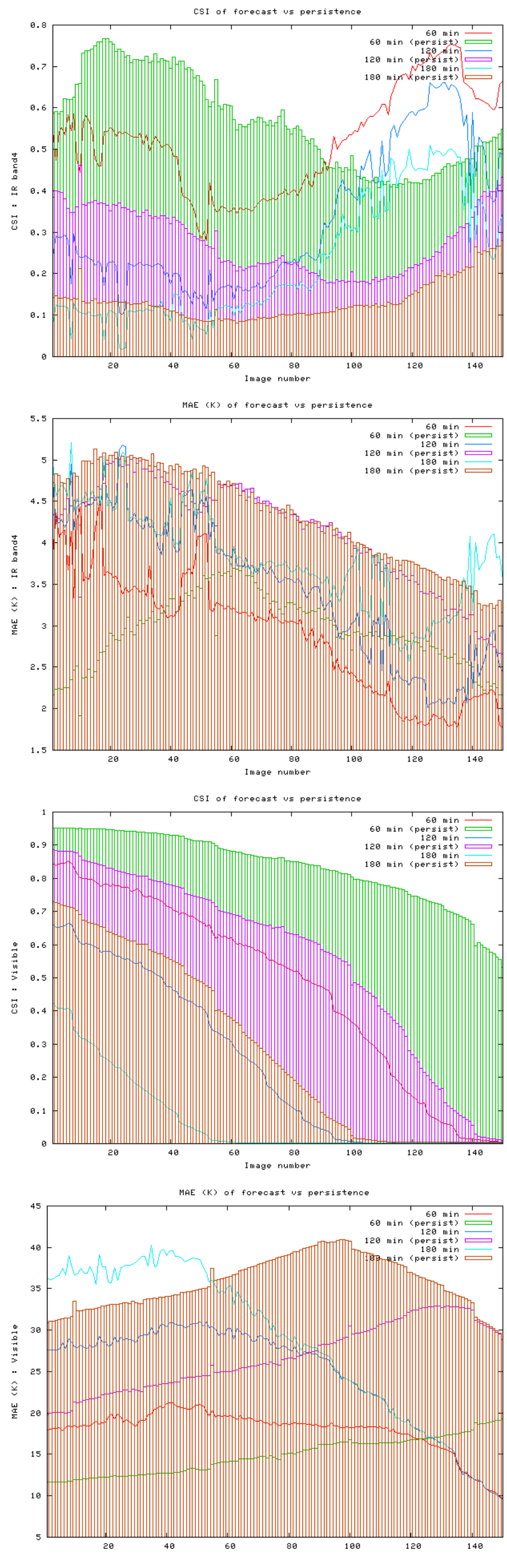

Figure 6: Skill at forecasting position and intensity of storms in infrared and visible imagery over time, as compared to a persistence forecast

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